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Isolated States of America: The Impact of State Borders on Mobility and Regional Labor Market Adjustments

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ABSTRACT

I document a new empirical pattern of internal mobility in the United States. Namely, county-to-county migration and commuting drop off discretely at state borders. People are three times as likely to move to a county 15 miles away, but in the same state, than to move to an equally distant county in a different state. These gaps remain even among neighboring counties or counties in the same commuting zone. This pattern is not explained by differences in county characteristics, is not driven by any particular demographic group, and is not explained by pecuniary costs such as differences in state occupational licensing, taxes, or transfer program generosity. However, county-to-county social connectedness (as measured by the number of Facebook linkages) follows a similar pattern. Although the patterns in social networks would be consistent with information frictions, nonpecuniary psychic costs, or behavioral biases such as a sate identity or home bias, the data suggest that state identity and home bias play an outsized role. This empirical pattern has real economic impacts. Building on existing methods, I show that employment in border counties adjusts more slowly after local economic shocks relative to interior counties. These counties also exhibit less in-migration and in-commuting, suggesting the lack of mobility leads to slower labor market adjustment.

JEL Classification Codes: J6, R1

Key Words: Internal migration, commuting, social networks, border discontinuities

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1 Introduction

The United States has traditionally been seen as a highly mobile country, with nearly one in five people changing their county of residence every five years. Even though internal migration has steadily declined over the past 40 years, the United States still exhibits higher internal mobility than most European countries (Molloy et al., 2011). Geographic mobility is often viewed as both a chance for individuals to find better job opportunities and a mechanism through which places adjust to local economic shocks, contributing to labor market fluidity and economic dynamism (Blanchard and Katz, 1992; Molloy et al., 2016). However, there is significant heterogeneity in local economic conditions across the country. Most counties are within 60 miles of another county that has higher average wages, lower average house prices, or both (Appendix Table A1). Although there might be other local characteristics that offset these raw spatial differences, it seems plausible that many individuals could encounter employment or housing "opportunities" through short distance mobility, either migration or commuting. Frictions that reduce or limit internal mobility could lead to less dynamic local economies.

I document a previously undocumented aspect of U.S. internal migration and commuting that has implications for labor market fluidity and dynamism. Using the Internal Revenue Service (IRS) county-to-county migration data, and Longitudinal Employer-Household Data (LEHD) Origin Destination Employment Statistics (LODES) data on county-to-county commute flows, I show that even conditional on distance, county-to-county migration and commute flows drop significantly when a state border lies between the two counties. People are three times as likely to move to a different county in the same state than to an equally distant county in a different state. People are about twice as likely to commute to a different county in the same state as to an equally distant county in a different state. In other words, state borders reduce both long-term and temporary human mobility. In this paper, I document the extent of these empirical patterns, explore potential explanations for why this cross-border drop in mobility exists, and evaluate how this empirically evident mobility friction impacts the way local labor markets adjust to cyclical economic shocks.

The canonical migration choice model suggests that a discontinuous drop in migration rates at state borders could be due to either differences in location-specific utility or differences in moving costs. This does not appear to be the case. As I document, the gap in migration and commute rates associated with state borders does not appear to be driven by differences in local characteristics that could drive differences in utility. The cross-border mobility gap does not close if I control for origin and destination fixed effects or even if I control for differences between the origin and destination in labor market characteristics, industry composition, demographic composition, natural amenities, political leaning, home values, or local test scores. Furthermore, this gap persists when I focus on counties that we would traditionally think of as being more interconnected and similar, such as counties in the same metropolitan statistical area (MSA) or commuting zone (CZ) or even neighboring counties on state borders.

Differential changes in pecuniary costs at state borders from state-level regulation, such as differences in occupational licensing, state income taxation, or state transfer policy, also do not explain the mobility gap. Because the discontinuity is present for both migration and commute flows, it likely is not driven by pecuniary adjustment costs associated with moving across state lines (e.g., updating vehicle registration or driver's licenses). In American Community Survey (ACS) microdata, cross-border migration and commute rates do not statistically differ across most demographic groups (i.e., age, race/ethnicity, gender, employment, or family structure), suggesting that differences in the preferences or costs across these groups do not explain the pattern. There are, however, distinct differences based on whether or not the individual was initially residing in his or her birth state. Among those who moved in the past year, individuals originally living in their birth state are over 60 percent less likely to move out of state than people in the same local area who were born in a different state.

Consistent with origin ties and county-to-county connectedness playing a role, I find a similar geographic discontinuity in Facebook friendship rates across state borders, as captured by the Social Connectedness Index (Bailey et al., 2018). On average, people have twice as many Facebook friends in a same-state county 15 miles away as in a cross-border county 15 miles away. When I control for the Facebook network linkages between the origin and destination, the decrease in migration and commuting associated with state borders falls substantially, suggesting that most of the discontinuity in mobility is empirically explained by social network strength or something correlated with the social network.

Although causality could run in both directions, the correlation between cross-border mobility and network strength is consistent with three county-to-county connectedness augmentations of the simple migration model. First, weaker social networks across state lines could impose additional nonpecuniary, psychic costs associated with moving (such as leaving personal ties to community, friends, and family). Second, weaker social networks across the border could also lead to more information frictions, leaving individuals less informed about the potential costs and benefits of moving across state lines. Finally, discontinuous drops in social ties across the state border could also arise if a third factor, like behavioral biases such as home bias or state identity, simultaneously keeps people from moving and making social connections across state lines. A strong state identity could affect mobility, regardless of the presence of local ties to family and friends.

Both psychic costs and information frictions would imply that state borders reduce migration flows because their placement is correlated with people's network borders. This does appear to be the case. Using connected communities, as defined by Bailey et al. (2018), to capture contiguous regions of strong county-to-county friendship linkages, we see that connected community borders often approximate state borders, although there are places where the state borders and network borders deviate. In a horse-race regression allowing both the actual state border and the social network border to have separate impacts, most of the effect loads on the actual state borders, explaining 3–6 times as much as the social network borders. This pattern is inconsistent with the psychic cost of abandoning personal ties or information frictions due to weak social ties being the main drivers of the drop in mobility precisely at state borders.

There is, however, suggestive evidence that state identity is not only common but that it influences migration decisions. Analysis of Pew Research Center data on mobility (Pew Research Center, 2009) suggests that as much as 68 percent of people "identify" with their birth state. Among survey participants, exhibiting a birth-state identity reduces the likelihood of ever leaving one's birth state by 35.3 percentage points (nearly 64 percent) and increases the preference to live in one's birth state over all other states by 28.1 percentage points (80 percent). In response to hypothetical questions about moving, people with a birth-state identity who currently live in their state of birth are significantly less likely to consider a move. In contrast, exhibiting a birth-state identity has no impact on the probability of making a move if the individual is currently living outside their state of birth. This is consistent with an endowment effect in migration, where birth-state identity imposes additional costs for moves out of the originally endowed birth state. Importantly, these patterns persist even when controlling for individuals' family ties or ties to amenities in the area they currently live in, suggesting birth-state identity is a factor independent of other local ties.

This work builds on existing research exploring the role of local ties (Zabek, 2020), rootedness (Kosar et al., 2020), and migration costs (Desmet et al., 2018). Using a spatial equilibrium framework, Zabek (2020) finds that local ties tend to keep people near their birthplace, leading to muted migration responses to local economic shocks. In this work, "local ties" is a conceptual term, meant to capture the concept that people tend to live near their birthplace for unexplained reasons, with little evidence of what creates the local tie. As I document, people not only tend to stay near their birthplace, but they are significantly less likely to leave their birth state, even if they live close to the state border. Although local ties could reflect the psychic cost of leaving friends and family, the analysis here suggests that this is not what drives hesitancy to cross state borders. Rather, state borders seem to have a separate effect, potentially driven by home bias or state identity. This identity appears to have a distinct effect from family and other personal ties. Kosar et al. (2020) used stated-preference survey methods to document how various costs, including nonmoney costs, affect people's preferences about migration. They find that nonmoney moving costs are large, especially for individuals who self-identify as "rooted" to their location. State identity could contribute to these large nonmoney moving costs. Spatial economic models also highlight the role of migration costs, but this is often an all-encompassing term meant to capture the fact that there are regional wage differences that are not equalized by migration (Desmet et al., 2018). In this work, I shed light on what might be driving these migration costs and highlight the relative isolation of states.

Regardless of the mechanism behind the empirical pattern, this feature of U.S. internal migration affects the dynamic adjustment of labor markets to local shocks. Following existing methods exploring the economic recovery from the Great Recession (Hershbein and Stuart, 2020), I show that counties at the state border, where this mobility friction is plausibly more binding, see weaker recoveries in employment. Ten years after the initial cyclical shock, employment measures in border counties have recovered approximately 40 percent less than other counties in the same state. Border counties also see significantly less in-migration and in-commuting during the recovery period, leading to persistently worse labor market outcomes. Proximity to state borders leads to differences in local labor market dynamism and affects the ability of labor markets adjust to local cyclical shocks. Cross-state labor markets appear to be less connected than we might expect, a priori, potentially contributing to the persistent geographic heterogeneity in labor market conditions and economic mobility (Chetty et al., 2014) observed across the United States.

2 County-to-County Mobility Data

Unlike many other developed countries, the United States does not maintain administrative residential histories. To document patterns of internal migration and related trends, I use several sources, which I briefly outline here, with full details in the data appendix. The annual IRS Statistics of Income (SOI) county-to-county migration flows data are constructed by tracking the number of tax units and tax exemptions (to proxy for households and people) that change their tax form 1040 filing county from one filing year to the next. I divide the number of exemptions by the origin county population (in thousands) to measure the number of migrants per 1,000 people.

To capture county-to-county commute flows I use the LEHD Origin Destination Employment Statistics (LODES). These measures are constructed from LEHD microdata derived from unemployment insurance wage records. For over 90 percent of workers in the wage records, place of residence and place of employment are recorded, allowing the construction of publicly available county-to-county flows. I divide the number of workers by the county population to measure the number of commuters per 1,000 people.

Because the IRS data do not provide migration flows for subpopulations, I supplement this data with migration microdata from the 2012–2017 annual American Community Survey (ACS).[1] The ACS surveys over one million US households each year and documents individual and household measures ranging from household structure and demographics to employment and place of residency in the previous year.[2] I use the ACS microdata to examine migration and place-of-work differences across individual characteristics, like demographics, occupation, and place of birth.

To understand the impact of state borders on social networks, I use the Social Connectedness Index (SCI) which maps county-to-county Facebook friendship networks Bailey et al. (2018). This data takes a snapshot of active Facebook users in 2016 and reports the number of Facebook friends in each county pair, scaled by an unobserved scalar multiple to maintain privacy. I supplement these data with annual Surveillance, Epidemiology, and End Results (SEER) county population counts and state policy data from various sources. Each of these

[1]The LODES provides flows for subgroups, but only by broad age, education, and industry categories.

[2]I do not use data from earlier years, because the smallest geographic measure, public use microdata area (PUMA) definitions, were updated in 2012.

sources is documented in full in the data appendix.

3 County-to-County Mobility: The Empirical Pattern

3.1 State Borders and County-to-County Migration and Commuting

The relationship between distance and migration rates has long been documented (Schwartz, 1973). Average migration rates drop smoothly as the distance between an origin and a potential destination increases. However, even in the raw IRS migration data, the magnitude of this pattern depends on whether the origin and destination counties are in the same state. In Figure 1, I plot the average number of migrants per 1,000 residents of the origin county, in 2017, in one-mile bins for all county pairs in the continental U.S., with population centroids 15–60 miles apart.[3] These average migration rates are plotted separately for county pairs in the same state, and county pairs separated by a state border. Both within-state and across-state migration rates fall as distance increases, but there is a gap in levels. At the same distance, migration rates to same-state counties are approximately three times as high as migration rates to cross-state counties. The pattern is similar when looking at county-to-county commute rates: conditional on distance, commute rates are approximately twice as high among same-state county pairs relative to cross-border pairs. State borders are associated with raw differences in both residential and employment mobility. This is the first work examining the role of state borders on human mobility and is consistent with work suggesting that state borders impose large trade barriers (Coughlin and Novy, 2012).

The first goal of this paper is to unpack these patterns to determine whether the state border discontinuity is significant, and whether it is sensitive to other potential mediation factors. As such, I will estimate the following parameterized version of the above analysis

[3] I focus on these "close" county pairs because there is sufficient coverage of both within-state and cross-state pairs. There are no cross-border county pairs that have population centroids less than six miles apart. I restrict to county pairs at least 15 miles apart to avoid comparisons with few observations. I also limit to counties 60 miles or less apart to avoid a compositional shift from typically sized counties to large states and counties in the West. The pattern is similar if I include county pairs that are closer or farther away (Appendix Figure A4).

throughout:

$$Y_{od} = \sum_{b=15}^{59} \beta_b(\textit{Diff. State*b Miles Apart}) + \gamma_b(\textit{b Miles Apart}) + \varepsilon_{od} \tag{1}$$

The outcomes of interest are the origin/destination specific number of migrants per 1,000 people at the origin and the origin/destination specific number of commuters per 1,000 people. The explanatory variables are the interactions between an indicator for whether the counties are in different states and a vector of one-mile-distance bin indicators. The 60-mile bin is omitted as the reference group. Average migration rates among counties 60 miles apart are quite low, with only about one migrant per 10,000 people. The γ_b coefficients trace out the migration/commute rates for counties in the same state, while the β_b coefficients indicate how much lower the migration/commute flows are for counties that are in the same distance bin, but in a different state. Standard errors are corrected for clustering at the origin county level. Throughout, I present the coefficients graphically, with the γ_b coefficients and the total effect for counties in different states ($\beta_b + \gamma_b$) plotted with 95 percent confidence intervals. These point estimates are provided in Appendix Figure A1 and match the means estimated in Figure 1, since migration and commuting levels in the omitted group is approximately zero. I use the final-year that IRS migration data are available, 2017, so there is only one observation per origin/destination pair. But, as seen in Appendix Figure A2, the state-border discontinuity is similar for all years available in the data—the years since 1992 for migration and 2003 for commuting.

This flexible parameterization does not impose strong assumptions on the way distance impacts mobility, but it also does not provide a concise estimate of how state borders reduce mobility. To distill the impact of state borders on migration and commute rates into a single parameter, I will estimate the ratio of area under the curve for cross-state county pairs relative to the area under the curve for within-state county pairs using Riemann integration across the one-mile-distance bins. From the baseline estimates in Figure 1, state borders reduce migration rates by 72 percent for county pairs between 15 and 60 miles apart. This gap is significant, with 95 percent confidence intervals of 68 and 76 percent. There is a similar 74 percent reduction in commute rates.

Sensitivity to Controls

Counties across the country differ on many dimensions, which are not controlled for in the previous equation and could potentially explain the cross-border differences in mobility. To test the sensitivity of the state-border discontinuity, I adjust Equation (1) to include origin fixed effects to control for characteristics of the origin; destination fixed effects to control for characteristics of the destination; and observable origin/destination pair–specific differences in local labor market, population, housing market, and local amenity measures to control for pairwise differences as follows

$$Y_{od} = \sum_{b=15}^{59} \beta_b(\textit{Diff. State*b Miles Apart}) + \gamma_b(\textit{b Miles Apart}) + X'_{od}\Gamma + \phi_o + \delta_d + \varepsilon_{od} \quad (2)$$

The X_{od} vector includes differences in origin and destination labor markets (unemployment rates, employment-to-population ratios, average weekly wages, number of establishments, and industry shares); differences in the total population, as well as differences in the gender, racial, ethnic, and age composition of the origin and destination; differences in natural amenities such as the average temperature in January and July, average sunlight in January, average humidity in July, and USDA natural amenity score; differences in the 2016 presidential Republican vote share; differences in average home value; and differences in average math and reading standardized test scores from the Stanford Education Data Archive (SEDA) (Fahle et al., 2021). As seen in Figure 1 and throughout the paper, controlling for demographic, economic, local amenity, and housing market differences between the origin and destination (the lighter plotted points with confidence intervals) does not close the gap. State borders are still associated with a 67 percent reduction in migration rates and a 76 percent reduction in commuting.

Sensitivity to Measurement of Distance

Comparing the direct distance between county population centroids might provide the wrong comparison. If cross-state road networks are more sparse, or if state borders correspond with natural features likes rivers (as is the case for at least one county in 41 states), travel across state lines might be more costly, even if equidistant. However, if I calculate the GPS travel time between each county pair and estimate Equations (1) and (2), but measure distance in terms of minutes of travel, the role of state borders is similar (left panel of Figure 2).[4]

Sensitivity to Sample Composition

The pattern is not driven by compositional differences between the pairs of same-state and cross-state counties in the sample. Omitting counties without a cross-border county pair within 60 miles (see the map in Figure A3), like those in central Texas or Michigan, does not affect the distance gradient and state-border penalty is essentially unchanged (Figure 2).[5] The gap persists if I exclude county-to-county flows of zero (Appendix Figure A6),[6] and is present across the Northeast, Midwest, and South (Appendix Figure A7), with some evidence in the West where counties are large.

Furthermore, the pattern persists when focusing on county pairs we *ex ante* expect to be close and economically connected. In Figure 3 I plot the coefficients from Equation (2) but limit the sample to county pairs in the same commuting zone, in commuting zones that cross state borders (left panel), county pairs in the same cross-border metropolitan statistical area (MSA) (middle panel), or neighboring counties on state borders (right panel).[7] Even with

[4]As seen in Appendix Figure A9, the state border penalty is similar for counties separated by land or by rivers.

[5]Throughout the rest of the analysis I will impose this restriction to avoid compositional changes, but the patterns are unchanged if we include all county pairs within 60 miles of each other.

[6]The IRS data are censored for privacy, so county-to-county flows below 20 are not provided. As such, these flows are treated as flows of zero.

[7]When looking at neighboring counties, distance is restricted to 45 miles or less, as there are very few neighboring counties with population centroids more than 45 miles apart. Among the subsample of

these considerably smaller samples, there is still a significant reduction in migration and commuting associated with the state border. State borders are associated with a reduction in county-to-county mobility, even among places that we would expect to be similar or by construction connected.[8] As seen in Appendix Figure A8, this pattern also holds for individual MSAs, even when we focus on counties in well-known cross-state MSAs like New York City; Washington, D.C.; or Kansas City.

This pattern has not been documented previously and is perhaps unexpected, as there are no legal or residency restrictions associated with state borders (as there are with national borders) and since the U.S. is seen as highly mobile relative to other countries (Molloy et al., 2011). Given that this empirical pattern exists, the remainder of this paper explores potential mechanisms behind the state-border discontinuity in mobility and documents to what extent this empirical feature of mobility impacts the dynamism of local labor markets in the wake of local economic shocks.

4 Potential Explanations

To codify potential explanatory mechanisms, I turn to the canonical model of migration choice that builds on the early work of Sjaastad (1962). In its simplest form, the decision to migrate is characterized as a comparison between the utility gain and the cost associated with moving from origin o to destination d, as follows:

$$Move_{iod} = \begin{cases} 1 & if\; u_i(X_d) - u_i(X_o) \geq c_{iod} \\ 0 & else \end{cases} \tag{3}$$

neighboring counties, standard errors are large when using one-mile bins. This is because there are relatively few observations in each one-mile bin. The differences are more precisely estimated when larger bins that contain more observations are used.

[8]The pattern is similar if I restrict the sample to counties in the same Designated Market Area (DMA), which captures television broadcast media markets (Appendix Figure A5).

where utility is a function of location-specific characteristics. The migration rate from o to d can be captured as the share of the population at o for whom

$$c_{iod} < c^*_{iod} = u_i(X_d) - u_i(X_o). \tag{4}$$

Even in this simple representation of the migration decision, there are several places state borders could arise. First, discrete changes at state borders in local characteristics that contribute to utility would result in corresponding discrete changes in migration propensities and migration rates. Second, discontinuities in moving costs between the origin and destination d at state borders would also affect migration propensities.[9] Both potential mechanisms are plausible. Although spatial equilibrium models (Roback, 1982; Rosen, 1979) highlight the role of migrants in equalizing differences across places, moving costs are prohibitively large for many individuals (Bartik, 2018; Kosar et al., 2020), and there is still substantial heterogeneity in labor market and housing market conditions across geography (Bartik, 2018). Economic geography models that do incorporate moving costs (Desmet et al., 2018; Redding and Rossi-Hansberg, 2017) often indirectly inferred these costs from differences in population and migration rather than tying them to institutional or social features.

It is also possible that the model in Equation (3) is too simple. Alternative mechanisms, such as psychic costs, information frictions, or behavioral biases, not captured in the model above, might also come into play by "tying" or "connecting" counties together. If state borders influence these parameters, discrete changes in migration rates could also arise. Building on this theory and previous work exploring the drivers of migration behavior, I next explore the role of leading potential mechanisms.

[9] Adding multiple potential destination turns the decision into a multinomial decision in which the individual chooses the destination where $u_i(X_d) - u_i(X_o) - c_{iod}$ is the largest. For state borders to matter, the same potential channels are present, but the relative importance of these channels in other potential destinations will also matter.

4.1 Differences in Utility

Discrete changes in labor market opportunities, demographic characteristics, amenities, or housing markets at state borders could result in discrete differences in utility across state borders. In the language of spatial economics, discontinuous changes in both exogenous (geographic features) and endogenous (economic and social features) amenities at state borders could explain the pattern (Redding and Rossi-Hansberg, 2017). Controlling for observable differences in these characteristics does not eliminate the discontinuity in migration or commuting at the state border (Figure 1), suggesting they do not drive the predictive power of state borders. The pattern also persists when limiting the sample to counties in the same commuting zone, MSA, or even among neighboring counties, where we would expect counties to be more similar.

To further rule out discrete changes in local characteristics, I examine how average characteristics in 2017 change as the distance between origin and destination decreases. I examine all of the same measures controlled for in Equation (2). For each county pair there are flows in two directions, so by construction, differences between the origin and destination by distance will be mean zero. For this reason, I examine a more conservative measure of absolute differences in county pair characteristics. I examine origin/destination differences in measures that are frequently used as controls (or outcomes) in labor market and demographic research. I examine labor market measures (the unemployment rate, employment-to-population ratio, average weekly wages, number of establishments); industry shares (shares in natural resources and mining, construction, manufacturing, trade, information, finance, professional, education and health, hospitality, public sector, and all others); demographics (total population, share female, non-Hispanic White, non-Hispanic Black, non-Hispanic other, Hispanic, under 20, 20–34, 35–49, 50–64, and 65 and older); natural amenities (January average temperature, January average sunlight, July average temperature, July average humidity, and the USDA natural amenities scale); the 2016 presidential Republican vote share; the county housing price index, converted to dollars using the median house value from 2000; and the county average standardized math and reading/language arts test score for third through eighth grade (averaged over 2008–2017), obtained from SEDA (Fahle et al., 2021). These plots are presented in Appendix Figures A10 and A11. As noted above, my analysis focuses on county pairs that are between 15 and 60 miles apart because there are few county pairs less than 15 miles apart. For each measure, I shade in gray origin/destination pairs that are less than 15 miles apart. Consistent with there being few observations within 15 miles of each other, the spread increases and standard errors on the local linear polynomials become large as the distance falls below 15 miles.[10] If we focus on counties 15 to 60 miles apart, differences in average local labor market, demographics, local amenities, vote share, or housing market measures appear similar regardless of a state border separating the counties.

4.2 Differences in Pecuniary, Moving Costs

There are many pecuniary costs associated with moving (e.g., renting a moving truck or hiring movers). Most of these would be incurred whether the move was across a state border or not. However, there are some pecuniary costs associated with moving that differentially impact in-state and cross-state moves. For example, you are required to renew your license and car registration when you move to another state, but not if you move to a different county in the same state. Similarly, state policies might lead to differential pecuniary costs associated with cross-state moves.

The costs faced when considering residential moves (migration) and employment moves (commuting) often differ. For example, commuters can cross state lines without incurring adjustment costs associated with moving (such as updating registration), but they still face some costs, such as state-level taxation. Because the pattern for migration and commuting is similar, the impact of state borders is likely not solely driven by pecuniary adjustment costs.[11] However, I explore the potential role of several policy-induced mobility costs that

[10] This fact is further highlighted in Appendix Figure A12, where each point is weighted by the number of county pairs.

[11] One potential adjustment cost commuters would still face is the ease with which they can cross the border. This might be particularly challenging if the state border follows a river and there are limited

have been highlighted in the internal migration literature and could affect both migration and commuting.

Occupational Licensing

Some states require licenses, certificates, or education/training requirements for someone to perform certain tasks or occupations.[12] In some cases, these requirements do not include state reciprocity, meaning a qualification in one state is void in another. Johnson and Kleiner (2020) show that among 22 universally licensed occupations for which licensing exams are either state-specific or nationally administered, state-specific licensing rules reduce interstate migration by approximately 7 percent. However, they note that these effect sizes can only explain a small share of the aggregate time trends in interstate migration.

A comprehensive database of occupational licensing requirements across states and over time does not exist. Previous research exploring occupation licensing has had to rely on self-collected records state by state for available occupations (Carollo, 2020). Furthermore, states sometimes license tasks rather than occupations, making it hard to map licenses to occupation codes. To explore the role of licensure, I exploit the relatively new licensing measures available in the CPS.[13] Starting in 2015, CPS respondents were asked three questions about professional licensing: 1) Do you have a currently active professional certification or a state or industry license? 2) Were any of your certifications or licenses issued by the federal, state, or local government? and 3) Is your certification or license required for your job? Following Kleiner and Soltas (2019), I indicate that an individual's occupation is licensed by the government if he or she answers yes to the first and second questions. I then collapse the CPS data to the state by year and by four-digit occupation code to determine what share of

crossings. In Appendix Figure A9, I plot estimates from a specification similar to Equation (6), where states with and without river borders are treated separately. Overall, the border penalty is similar whether or not there is a river at the border.

[12] See Carollo (2020) and Kleiner and Soltas (2019) for a comprehensive treatment of the labor market and welfare impacts of occupational licenses.

[13] Results are similar if I instead use occupational licenses as captured by Johnson and Kleiner (2020) or the National Council of State Legislatures.

workers in a given occupation and state report that they have a government-issued license. As Kleiner and Soltas (2019) report, individual reports of licensure contain measurement error. Even in universally licensed occupations, only about 65 percent of workers are flagged as having a government license. To improve the signal of these measures, I will consider a more restrictive measure of occupational licensing (25 percent or more of the workers in the cell reported a government-issued license) and a less restrictive measure (over 10 percent).[14]

To determine whether occupational licenses produce the drop in migration and commuting at state borders, I explore cross-state migration and commute rates by occupational licensure status in the ACS and estimate the following relationship:

$$Y_{isot} = \beta Licensed\ Occupation_{isot} + \gamma_o + \delta_s + \phi_t + \varepsilon_{isot} \tag{5}$$

The outcomes of interest are a binary indicator that equals 1 if the individual moved out of state s in the past year and a binary indicator for whether the worker commutes out of state s (i.e., the place of work is in a different state). The explanatory variable of interest is the indicator *Licensed Occupation*, which equals 1 if the individual in year t is in an occupation (o) in which the share of workers in his or her state (s) that report having a license exceeds the prespecified threshold (25 or 10 percent). For migration, the state of residence in the previous year is used to determine licensure status. For commuting, the current state of residence is used. I explore specifications that only control for occupation fixed effects; occupation, state, and year fixed effects (as in Equation (5)), and occupation, state, and occupation-by-year effects. This last specification will compare workers in the same occupations in licensed and unlicensed states.

Results are reported in Table 1. Among the full population, being in a licensed occupation has no effect on moving out of state. Limiting the sample to those who move, to account for selection into moving, does not change the results. The coefficients are typically small,

[14]The CPS data does not explicitly separate federal, state, or local licenses. However, by including occupation by year-fixed effects, universal licensing practices will be absorbed, leaving only state and local licensure.

precise, and positive, suggesting that government-issued licensing has no systematic, negative effect on out-of-state migration. The pattern is similar for out-of-state commuting. Only one specification (including only occupation fixed effects) suggests a marginally significant 0.3 percentage point reduction in out-of-state commuting associated with occupational licensing.

I explore the impact of occupational licensing on migration and commuting further in Appendix Figure A13. First I restrict the sample to occupations that are licensed in at least one state but not all states. I then plot each occupation's share that moved in the last year on the x-axis, and the share that moved out-of-state on the y-axis, separately for licensed states and unlicensed states. Each occupation is weighted by the summed sampling weights for all of the workers in the cell. The linear relationship between these two migration shares for nonlicensed occupations is plotted in blue with 95 percent confidence intervals. In general, occupations that have a higher migrant share have a higher out-of-state migrant share. I then overlay the plot for cells that have a recorded occupational license. If low out-of-state migration was caused by occupation licenses, we would expect licensed occupations to be systematically lower on the y-axis. However, this is not the case: licensed occupations are not outliers, and, if anything, the linear relationship (in pink) for licensed occupations is steeper. Commute patterns are similar, although the slope for unlicensed occupations is significantly steeper, consistent with occupational licensing dampening cross-border commuting. Overall, there is little evidence that occupational licensing leads to the drop in migration across state borders, but some evidence that it could contribute to lower levels of cross-border commuting.

State Taxation

Taxation also varies across state lines, sometimes leading to large differences in tax burden across state borders. State income tax rates vary between 0.0 and 13.3 percent (Loughead, 2020), and there are also differences in sales tax and corporate tax rates across states. Moretti and Wilson (2017) find that high performing scientists' locations are sensitive to state tax differences, suggesting that differences in state taxation could explain the pattern around state borders.

However, if the discontinuity is driven by state-level taxation, we would expect asymmetric behavior, with migration border penalties between low-tax and high-tax states, and higher flows from high to low tax states. I estimate the following equation to determine if cross-border county-to-county migration rates differ when the move implies a larger or smaller tax burden relative to migration within the same state, where taxes are the same.

$$Y_{od} = \sum_{b=15}^{59} \beta_b(\textit{Higher*Diff. State*b Miles Apart}) + \theta_b(\textit{Lower*Diff. State*b Miles Apart}) + \gamma_b(\textit{b Miles Apart}) + X'_{od}\Gamma + \phi_o + \delta_d + \varepsilon_{od} \quad (6)$$

Higher indicates that the state income tax burden in the potential destination county is greater than the state income tax burden in the origin county. *Lower* indicates that the state income tax burden in the destination county is less than or equal to the burden at the origin. The β_b represents the differential mobility to counties in different states with a higher tax burden, while the θ_b represents the differential mobility to counties in a different state with a tax burden less than or equal to the origin county. Both of these are relative to mobility between counties in the same state (where state taxes are the same), so there are three mutually exclusive groups.

In Figure 4, I show whether migration and commuting patterns differ for cross-state county pairs with high-to-low and low-to-high income, sales, and corporate tax burdens. Using tax burden estimates from the NBER TAXSIM, I examine how the role of state borders differs for households that are married and filing jointly with two children and $75,000 of annual income in the left column. Conditional on distance, migration and commute rates to both higher and lower income tax destinations are lower than to counties in the same state. Furthermore, the patterns for high-to-low and low-to-high flows are not statistically distinguishable.[15] The patterns are similar for states' sales tax rates, shown in the middle column. The point estimates for commuting to counties in lower-sales-tax states are consistently higher (e.g., the border penalty is smaller), but not statistically different. The border penalty is no different for migration or commuting to counties in states with higher or lower corporate tax rates (right column). There is no consistent evidence that differences in state taxation drive, or mediate, the drop in mobility associated with state borders.

Spatial equilibrium models (Roback, 1982; Rosen, 1979) would suggest that long-standing differences in tax rates would lead to differential sorting, causing the utility value of areas to equilibrate across all dimensions. As such, we might not observe differences when examining equilibrium migration rates. However, the difference in tax burdens might vary across origin destination pairs or throughout the income distribution, meaning that for some subgroups, a move would be associated with a smaller tax burden, while other groups could experience a tax increase. For this reason, I also examine income tax burdens for various family types (single, married, with dependents) at multiple income levels to see whether certain subpopulations' mobility patterns respond (Appendix A15, A17, A16). I find that there are no systematic differences across any of the income levels or family types.

Additionally, turning to the ACS microdata, I can focus on differences in the household's specific tax burden associated with a potential move. For family units in the 2012–2017 ACS microdata, I use TAXSIM to calculate their income specific state and federal income tax burden. By moving the focus to a household, rather than a county-to-county migration flow, identifying the potential destination is not straightforward. To focus on the origin/destination decisions that *ex ante* are the most likely, I limit the sample to families originally living in commuting zones that cross state lines, and then calculate the average

[15] Even if tax rates are the same, filing state taxes across multiple states could impose another burden, potentially reducing mobility. Some states have state tax reciprocity agreements. For example, residents of Maryland who work in Virginia or D.C. will have Maryland state taxes withheld and thus only need to file taxes in Maryland (see Appendix for a full list of tax reciprocity agreements). As seen in Appendix Figure A14, the affect of state borders on migration and commuting is similar regardless of whether the origin and destination states have tax reciprocity agreements.

income tax burden the family would face in the other state(s) in the commuting zone.[16] I then calculate the percentage change in total federal and state income tax burden between the original state and the other state in the commuting zone.[17] In Appendix Figure A18, I plot the share of migrants who move out of state by the change in the total tax burden in one-percentage-point bins. If state income tax policy led to the reduction in migration across the state border, we would expect the share of migrants that move out of state to decrease as the income tax burden increases with a cross-state move. Instead, there is no significant relationship between the change in tax burden and the out-of-state migration share. Although some subpopulations might be sensitive to tax burden changes (such as star scientists (Moretti and Wilson, 2017)), it does not appear to drive the discontinuity at state lines.

State Transfer Policy and "Welfare Migration"

State transfer programs also differ, leading to discontinuities in potential low-income benefits at state lines. These can be thought of as negative costs or benefits associated with a move and could differentially affect the utility associated with a cross-border move. There is a long literature exploring interstate migration in response to state low-income benefit generosity, or "welfare migration." Gelbach (2004) find that low-income populations that move across state lines tend to move to higher benefit states, while Borjas (1999) documents a similar pattern among nonnative immigrants. McKinnish (2005) and McKinnish (2007) find higher welfare expenditures in high-benefit states on the border of high- and low-benefit states. Welfare-reform policy changes in the 1990s reduced interstate migration of less-educated unmarried mothers (Kaestner et al., 2003), while Medicaid expansions associated with the Affordable Care Act (ACA) did not increase migration to expansion states (Goodman, 2017).

[16] For commuting zones with multiple states, I compare the tax burden in the origin state to the average tax burden in the other states. The pattern is similar if I instead compare the maximum or minimum tax burden in the other states.

[17] As some states do not have an income tax, I consider the federal plus state income tax burden so percentages will be defined.

McCauley (2019) finds that migration to health-care benefits in the United Kingdom depends on access to information. The potential impact of welfare policy on commuting will depend on whether applicants must establish residency. For example, medicaid recipients must reside in the state of application, whereas state earned income tax credit (EITC) claimants only need to earn income and file taxes in the state.

Based on the existing work, I focus on two state transfer policies that affect low-income households and vary across state lines: ACA medicaid expansions and earned income tax credit (EITC) state supplements.[18] I also examine the role of the effective state or national minimum wage, another policy that impacts the income of low-income households. For each of these policies, I estimate a model similar to Equation (6), but $Higher$ and $Lower$ now reference the benefit generosity in the destination state relative to the origin state. These estimates are plotted in Figure 5. Migration and commute rates to cross-border destinations with higher minimum wages, higher state EITCs, and Medicaid expansions were not significantly different from migration rates to cross-border destinations with lower benefits, respectively. In all cases, cross-border migration was significantly lower than within-state migration, conditional on distance. Also, the differences between low-to-high and high-to-low benefit states are not significant, suggesting the discontinuity in migration across state borders is not driven by differences in state transfer policy.[19][20]

[18]Since welfare reform in 1996, benefit levels and enrollment in traditional cash welfare, Temporary Aid for Needy Families (TANF), have been very low, and thus unlikely to drive the aggregate pattern. For this reason, I only include the analysis in the appendix (Appendix Figure A19), with no significant differences.

[19]Although it is not a state transfer program, state-to-state differences in per-pupil public education spending could also drive differences in mobility. This likely captures state-level differences in both taxation and public spending. As seen in Appendix Figure A19 there is not asymmetric migration or commuting to out-of-state counties with higher or lower prekindergarten-through-twelfth-grade per pupil expenditures.

[20]In the LODES, I can also examine census-tract-to-census-tract-level commuting to see if county borders have a similar effect. Policy variation and costs such as taxes or registration requirements are generally controlled at the state level. However, I still observe a slight county border penalty in tract-to-tract commuting, suggesting something else is driving the pattern (Appendix Figure A21).

Differential Costs across Demographic Groups

Consistent with this evidence, cross-border mobility rates are similar across demographic groups that might face different adjustment costs or have different preferences. Using the 2012–2017 ACS microdata, I calculate the fraction of migrants that move across state lines for a range of demographic groups (Figure 6). Among migrants, the share that cross state borders is consistently between 15 and 22 percent across age, gender, race, employment status, marital status, family setting, home ownership, and immigration status groups.[21] There is an education gradient, with the share of migrants moving across state lines increasing with education. Federal employees are outliers, with roughly 43 percent of migrants moving across state borders, but otherwise there is no systematic pattern.[22] Consistent with the gap not being driven by pecuniary costs, we only see slightly lower out-of-state migration for families with children or school-age children, who face additional adjustment costs when changing school districts, or state and local employees who are more likely to have state-specific pension benefits. The overall pattern is similar when examining the share of commuters that commute across state lines. For migration, the group with the lowest point estimate consists of migrants that originally resided in their birth state, while migrants originally residing outside their birth state are more than twice as likely to move out of state. Out-of-state commute rates are also twice as high for workers residing outside their birth state, relative to those in their birth state.

I explore the role of birth-state residence further in Table 2 by estimating

$$Y_{ipt} = \beta \, \mathit{Originally\ in\ Birth\ State}_{ipt} + X_i'\Gamma + \delta_{pt} + \alpha_a + \gamma_o + \varepsilon_{ipt} \tag{7}$$

The outcome is whether or not individual i—originally living in state and Public Use Microdata Area (PUMA) p in year t—moved. PUMAs are the smallest publicly available

[21]The patterns are similar if I restrict the sample to migrants originally living in cross-state commuting zones (Appendix Figure A22).

[22]The federal employee share is similar if I exclude people initially in the Washington, D.C., area (D.C., Maryland, and Virginia).

measure of geography in the ACS. The explanatory variable of interest is the indicator *Orginially in Birth State*, which equals 1 if state-PUMA p was in the individual's state of birth. The PUMA by year fixed effects (δ_{pt}) makes this a comparison of individuals who originally were living in the same local area at the same time, to see if people living in their birth state respond differently, in terms of mobility, to local conditions than others living in the area. I will see how estimates differ when I include demographic controls (gender, race, marital status, number of children, and education), age fixed effects (α_a), and occupational fixed effects (γ_o). Since place of work and commuting are measured contemporaneously in the ACS, I replace *Originally in Birth State* with *Currently in Birth State* when examining commuting.

Among people in the same local area, individuals born in that state are 1.3–3.5 percentage points (9–23 percent) less likely to move at all, relative to individuals who were born in another state. However, conditional on moving at all, people in their birth state are about 5 percentage points (31 percent) more likely to move to a different PUMA within the same state but about 15 percentage points (63 percent) less likely to move out of state than individuals born elsewhere (Table 2). In other words, people living in their birth state are only slightly less likely to move at all, but significantly more likely to move out of the local area (but stay in state) and significantly less likely to leave the state. Residing in one's birth state also affects cross-border commute rates. Workers living in their birth state are 1.7–1.9 percentage points (11–13 percent) less likely to commute out of state relative to workers living outside their birth state. Thus, living in one's birth state appears to influence mobility across state borders, which could have large implications in aggregate, as approximately 52 percent of adults reside in their state of birth.

5 Connectedness: The Correlation Between Cross-Border Social Networks and Mobility

Less cross-border mobility of individuals in their birth state reiterates the potential role of connectedness and local ties. If county-to-county connections are stronger within state than across state, this could influence mobility rates. In Figure 7, I explore this further by estimating Equations (1) and (2) with the scaled number of Facebook friends between each county pair divided by the origin population as the outcome. This measure is known as the SCI and is constructed from a snapshot of active Facebook users in 2016. Like migration and commuting, there is a distance gradient in the number of Facebook friends, but once again, conditional on distance, friendship rates are significantly lower for cross-border county pairs than for counties in the same state. Including origin and destination fixed effects or differences in labor market, demographic, amenities, or housing markets between the origin and destination do not significantly impact the pattern.

Furthermore, controlling for the origin/destination Facebook friendship rate in addition to the other controls in Equation (2) considerably compresses the gap in migration associated with state borders (Figure 8). For close counties (15–25 miles apart), the gap falls from 3–6 migrants per 1,000 people to 0.5–2 migrants per 1,000 people. Interestingly, the distance gradient for cross-state pairs completely disappears when we control for the social network (consistent with Diemer (2020)), but there is still a slight distance gradient for same-state county pairs. The gap in commute rates associated with state borders completely disappears, as well as the distance gradient, suggesting that after controlling for the strength of social connections, state borders have no additional impact on commute flows.

First, it must be acknowledged that a causal relationship between migration, commuting, and social networks could go in either (or both) directions. Weaker social networks across state borders could impose large psychic costs or information frictions, leading to low levels of mobility. Alternatively, low levels of cross-border migration and commuting for other reasons could lead to more regional isolation and lower social network spread across state borders. The fact that social network strength can empirically explain most of the state-border discontinuity in mobility does not pinpoint a particular mechanism, but is consistent with several channels of effect. First, fewer social connections across state borders might impose large psychic costs and reduced mobility. For example, people might be less willing to move 20 miles away across the state border if they have fewer family or friends there. Second, weaker social networks across state borders might lead to less information about circumstances and opportunities across the state border, resulting in less mobility if people are risk averse. Finally, people could exhibit local ties (like state identity or home bias) that makes them less likely to move away and in equilibrium less likely to have social links across state borders.

5.1 Psychic Costs

Existing work suggests that the nonmoney, psychic costs associated with leaving social connections are large (Kosar et al., 2020). Local ties to friends and family can keep people in weak labor markets and lead to depressed migration levels (Zabek, 2020). The nonpecuniary, psychic cost mechanism implies a direction of causality. If social networks are weaker across state borders, for any reason, mobility across state lines will become more costly, leading to lower migration and commute flows. Psychic costs related to social ties, however, does not explain why the social network was weaker across state borders initially.

5.2 Information Frictions

Since social networks become more sparse across state lines, people might have less access to information about opportunities, differentially keeping people from fully understanding returns and conditions in counties outside of their home state. These frictions could keep people from following the behavior in Equation (3). Previous work has found that access to information about government programs increases welfare migration (McCauley, 2019) and information about labor demand shocks increases migration to economic opportunities (Wilson, 2020b). Kaplan and Schulhofer-Wohl (2017) argue that improved access to information has allowed people to avoid moves that result in low-quality matches and helped contribute to the decline in internal migration over the last 40 years. The information friction mechanism implies a similar causal direction as the psychic cost mechanism. Weaker social networks across state borders lead to less information about opportunities in markets across state lines, potentially reducing mobility flows. Without an exogenous source of information or change in the social network, we cannot disentangle the psychic cost/social ties mechanism from the information friction mechanism.

5.3 State Identity and Home Bias

Other behavioral biases and frictions might also exist. For example, people might exhibit a state identity that creates a "home bias," making it systematically more costly to move away from their home state. This can be viewed as a nonmoney migration cost but is potentially distinct from the psychic cost of leaving social ties. The presence of home bias is consistent with less cross-state mobility from people in their birth state and more cross-state mobility from people originally outside of their birth state. Importantly, the state identity mechanism would imply a different direction of causality relative to the other two mechanisms. A third factor (state identity) leads to both lower mobility and fewer friendship links across the state border. As such, it might be possible to separately test for these effects.

In general, the SCI does fall across state lines, but this is not universally true. There are cross-border areas with stronger friendship networks. This presents a setting in which to estimate the relative importance of these mechanisms in a horse race regression. Following Bailey et al. (2018), I construct "Connected Communities" based on the strength of the SCI. After prespecifying a number of clusters, Connected Communities are constructed by grouping contiguous counties into clusters in which the social ties are stronger within the cluster than if a county was attached to a different, neighboring cluster. As seen in Figure

9, when there are 50 connected communities, the cluster borders approximate state borders, but there are obvious differences where communities spill across state borders. For example, New England is grouped as one cluster, Arizona and New Mexico are merged, and northern Texas, Oklahoma, and parts of Kansas are combined into one Connected Community. There are similar cross-border aberrations when 25 or 75 Connected Communities are created.[23] This would suggest that in some areas, strong social ties permeate state borders. If I treat Connected Communities as pseudo states and reestimate Equation (2), but use Connected Community borders, we see that these pseudo borders have the same directional impact on migration and commuting (Appendix Figure A23). Conditional on distance, migration rates across pseudo borders are about one-third to one-half as high as migration within the Connected Community.

This provides an opportunity to test the relative explanatory power of state borders versus Connected Community pseudo borders. If the empirical pattern in mobility is driven by a drop in social network strength across state borders due to either psychic costs or information frictions, we would expect the cross-border drop in migration and commuting to load onto the Connected Community pseudo borders rather than the state borders. I modify Equation (2) to include the full set of different state-by-distance interactions *and* different Connected-Community-by-distance interactions to test the explanatory power of the two in a horse race regression. As seen in Figure 10, most of the effect loads onto the physical state border, rather than the Connected Community borders.[24] This is true for any prespecified number of communities, between 10 and 500 (Figure A25). This would suggest that the drop in mobility is less associated with the social network border than it is with the physical state

[23] Fifty Connected Communities include one each in Alaska and Hawaii, which are not presented on the map.

[24] Although state borders are precisely measured, community borders are inherently measured with error. This might result in community borders carrying less predictive power. Using Connected Community assignments between 25 and 75 clusters, I calculate the fraction of scenarios in which each county pair is assigned to the same cluster. I then weight each county pair observation by $(\mu - 0.5)^2$, where μ is the fraction of times (out of 51) that the counties are in a different Connected Community. As such, county pairs that have more consistent Connected Community assignments receive more weight, while pairs where the assignment changes (plausibly because they are close to a social network "border") are down-weighted. The results are similar (Appendix Figure A24).

border. As both psychic and information friction channels suggest that the gap is driven by weaker social networks, these mechanisms are not likely to explain the impact of state borders on migration and commute flows. Although psychic costs and information frictions undoubtedly influence migration decisions and flows, they do not appear to explain the drop in mobility at state borders.[25]

Theoretical Formulation

The empirical pattern is consistent with home bias or state identity. This could be interpreted in the context of the behavioral phenomenon of endowment effects. Individuals are "endowed" with an initial location (for example, their birth state), which impacts their total cost of moving or their willingness to pay for a move. If this bias was present, two individuals with identical preferences over local characteristics would have different migration propensities if one was born in the origin and the other was not. This bias could on average lead to lower mobility and weaker social networks across state borders. The role of loss aversion and endowment effects in mobility decisions is not a new idea, but the existing discussion is limited to loss associated with the physical home (Genesove and Mayer, 2001; Morrison and Clark, 2016; Schkade and Kahneman, 1998).

Consider the following extension of the migration choice model in Equation (3), above, for an individual who was born in or grew up in state S.

$$Move_{iod} = \begin{cases} 1 & \textit{if } u_i(X_d) - u_i(X_o) \geq c_{iod} + \tilde{c}_i(o,d) \\ 0 & \textit{else} \end{cases} \tag{8}$$

[25] The pattern is similar when considering other well-defined, nongovernment borders, such as time zones. Among the 10 states split by time-zone borders, county-to-county migration and commute flows between counties in the same state across time-zone lines do not experience the same penalty, even though there are potential economic costs associated with these borders (Appendix Figure A26).

where $\tilde{c}_i(o,d)$ is an individual specific nonlinear cost function, as follows:

$$\tilde{c}_i(o,d) = \begin{cases} \phi & \textit{if } o \in S \textit{ and } d \notin S \\ 0 & \textit{else} \end{cases} \tag{9}$$

The additional cost, ϕ, is only incurred if o is in the individual's initially endowed state S and d is not in S. So, if the individual is considering a move within state or is already outside state S, this additional cost is zero.

Consider an individual who exhibits a home-state identity and currently lives in origin o, a location in their birth state S. If there are two potential destinations, d and d', that have identical characteristics ($X_d = X_{d'}$), but d is in the birth state S and d' is in a different state,

$$c_{iod}* = u_i(X_d) - u_i(X_o) > u_i(X_{d'}) - u_i(X_o) - \phi = c_{iod'}* \tag{10}$$

The cost threshold for moving to d (in the birth state) is higher than the threshold for moving to d' (in a different state). As such, a larger share of the population at o would be willing to move to d than d', even though the two destinations are identical on observables. Note, however, that if o is not in the state of birth, the propensity to move to the two locations is identical. Home bias or state identity can generate an endowment effect that produces theoretical results that match the empirical patterns. Consistent with the phenomenon that people in the ACS microdata are less likely to move if they currently reside in their birth state, we would expect to observe that people with a home bias or state identity would be less likely to move out of state if they are currently living in their birth state. The home identity need not be linked to the state of birth, although this is often where people spend their formative years, and information on birth state is available in many data sets.

Empirical Evidence

A preference for one's own state and how this impacts migration is not captured in most surveys, making it difficult to test the relevance of this mechanism. To the extent possible, I explore three separate settings to document this relationship, both descriptively and, under certain assumptions, causally.

Gallup Poll State Preference. First, if the drop in mobility at state borders is driven by a state identity, we would expect the drop to be larger in places with a stronger state identity. In a 2013 Gallup poll, approximately 600 adults across all states were asked whether or not they would describe the state where they live as "the best," "one of the best," or "the worst" state to live in.[26] The share of residents who felt their state was "the best" varied across states. For example, 28 percent of Texas residents felt that Texas was "the best" state to live in, while only 3 percent of Rhode Island residents felt their state was "the best" (see Appendix Table A2 for a full list). Since this measure is fixed across origin county, it is directly absorbed in origin county fixed effects. However, I can estimate how this measure interacts with the impact of state borders on county-to-county migration and commute flows by modifying Equation (2) as follows:

$$Y_{od} = \beta_1 \textit{Diff. State} + \beta_2 \textit{Diff. State*Share Feel State is ``the Best''}_s + \sum_{b=15}^{59} \gamma_b(b \textit{ Miles Apart}) + X'_{od}\Gamma + \phi_o + \delta_d + \varepsilon_{od} \quad (11)$$

In this regression, I still flexibly control for distance, but only the average effect of being in a different state for counties 15 to 60 miles apart is estimated. This parametric restriction allows for more precision than mile-by-mile estimates. I then interact state borders with the share of residents who felt their state was "the best" to test whether the state border has more or less predictive power in states that appear to have a stronger state identity.

[26] Survey results were released here: `https://news.gallup.com/poll/168653/montanans-alaskans-say-states-among-top-places-live.aspx`.

Consistent with the border penalty in Figure 1, being across a state border is associated with 0.6 fewer migrants and 5.3 fewer commuters per 1,000 residents (columns 1 and 3 of Table 3). When we interact this with state identity, we see that the state border is not associated with any change in migration for counties in states with no state identity (e.g., 0 percent of respondents think their state is "the best"). However, a 10 percentage point increase in the number of respondents who think their state is "the best" is associated with 0.9 fewer migrants per 1,000 residents to cross-border counties. For commuting, the direct effect of state borders is smaller when interacting with state identity but is still significant, and the strength of the origin state identity leads to significant reductions in commuters across state borders. This descriptive evidence is consistent with state identity contributing to the drop in mobility at state borders.

Pew Research Poll State Identity. As we saw in the ACS microdata, residing in your birth state is associated with only a slightly smaller probability of moving overall, but a substantially lower probability of moving out of state. However, this cannot solely be attributed to a birth state identity or home bias, as family ties can also be at play. Fortunately, in 2008, the Pew Research Center conducted a survey on individual mobility (Pew Research Center, 2009). This survey asked over 2,000 people about their moving history, asked about the places that they identify with and why, and presented hypothetical moving scenarios. As such, it is possible to observe how many people identify with their birth state and whether this identity is associated with the stated and revealed preference about moving, independent of other more studied phenomena like personal ties (Zabek, 2020) and the draw of amenities (Kosar et al., 2020).

Unfortunately, individuals in the survey who had moved and those who had not are asked slightly different questions. Individuals who had moved are asked, "You mentioned that you have lived in other places. When you think about the place you identify with the most—that is, the place in your heart you consider to be home—is it the place you live now, or is it some other place?" If the individual answered someplace else—or answered yes to the follow-up question, “Is there a place where you have lived that you identify with almost as much as where you live now?”—they were asked to identify the place and the *state* of that place. Based on these measures, I identify movers who exhibit a birth-state identity or say they identify with their birth state.

Individuals who had never lived away from their local community were asked separate questions. Nonmovers were asked to identify whether various factors were a “major reason,” “minor reason,” or not a reason they have not moved. In particular, nonmovers were asked about factors related to local, personal ties (i.e., family ties, connections to friends, or community involvement), local attributes or amenities (i.e., job or business opportunities, cost of living, the climate, a good place to raise children, recreation and outdoor activities, medical or health reasons, or cultural activities), or identity and attachment to the region (i.e., “no desire to live someplace else,” “I just feel I belong here,” or “I grew up here”). I classify nonmovers as exhibiting a birth state identity if they listed one of the three identity factors as a “major reason” they have not moved. Overall, 59.2 percent of movers are classified as having a birth state identity, as well as 81.4 percent of nonmovers. This averages out to an overall level of 68 percent.

Using this data, I estimate the relationship between having a birth state identity and attitudes towards migration as follows:

$$Y_{is} = \beta Birth\ State\ Identity_i + X_i'\Gamma + \delta_s + \varepsilon_i \tag{12}$$

The outcomes of interest are measures of migration for individual i in state s. *Birth State Identity* is defined as described above. I control for age and age squared, as well as for fixed effects for gender, race, ethnicity, and education. Current state-of-residence fixed effects are also included. Estimates are weighted using the provided survey weights, and standard errors are corrected for clustering at the current state-of-residence level. I extend this equation in two ways. First, I include indicators for whether the individual reports familial ties or local amenities (e.g., labor market, schools, cultural amenities) as a major reason that person lives where he or she currently does, to verify that state identity has an independent effect and is not simply colinear with familial or amenity ties. Second, I interact the birth-state identity measure, as well as the family and amenity ties measure, with an indicator that equals 1 if the individual currently resides in his or her birth state. Consistent with the endowment-effect model, I can test if birth-state identity impacts migration attitudes differently when someone currently lives in his or her birth state. This is estimated as

$$\begin{aligned} Y_{is} = \beta_1 \textit{Birth State Identity}_i + \beta_2 \textit{Birth State Identity}_i * \textit{In Birth State}_i \\ + \beta_3 \textit{Family Ties}_i + \beta_4 \textit{Family Times}_i * \textit{In Birth State}_i \\ + \beta_5 \textit{Amenity Ties}_i + \beta_6 \textit{Amenity Ties}_i * \textit{In Birth State}_i \\ + \beta_7 \textit{In Birth State}_i + X_i'\Gamma + \delta_s + \varepsilon_i. \quad (13) \end{aligned}$$

Having a birth-state identity is associated with differences in migration history and stated preferences (Table 4). People with a birth preference are 35.3 percentage points less likely to ever have left their birth state (a 64 percent reduction at the mean), and 28.1 percentage points (80 percent) more likely to say that the place they would prefer to live is in their state of birth. If I control for whether an individual reports that the reason for being where they are is due to family ties or local amenities, the impact of birth-state identity on ever leaving one's birth state is almost the same, at 32.8 percentage points, suggesting the effect of birth-state identity is not simply colinearity.

Birth-state identity also reduces people's stated preferences about moving. Overall, individuals with birth-state identity are no less likely to report that they are likely to move, but individuals with birth-state identity that *currently reside* in their birth state are 13.1 percentage points (35 percent) less likely to move. Even when controlling for having family ties or ties to local amenities in their current residence, being in one's birth state with a birth-state identity is still associated with a 12.3 percentage point reduction in the likelihood of moving. The pattern is similar when respondents were asked about moving to certain cities. Overall, having a birth-state identity is not associated with a lower propensity to state that they would move, but having a birth-state identity and residing in one's birth state is associated with an 8.4–9.0 percentage point reduction in being willing to move. This is consistent with a home bias that makes out-of-state moves away from the home state more costly, relative to other moves. Given the large share of individuals that exhibit birth-state identity and that reside in their birth state, this could explain a significant decline in migration across state borders. The tie to an initial state of residence could reflect a home bias that keeps people from moving across state borders, introducing a behavioral bias into the migration choice model.

PSID Sibling Comparison. The proceeding evidence on birth-state identity and home bias is correlational and suggestive. However, I can corroborate this evidence with a quasi-experimental approach. Using the Panel Study of Income Dynamics (PSID), I compare the mobility patterns of siblings. This within-family comparison allows me to control for shared unobservables of siblings. First, I identify families that move between children's births, so that one sibling is living in his or her birth state at age 16 and the other sibling is not. I then compare these children's propensity, once they reach adulthood, to move away from the state they resided in when they were 16. If state identity (in this case, birth-state identity) and endowment effects matter in the migration decision, the sibling who does not reside in his or her birth state at age 16 would not incur the extra cost of leaving his or her initial endowment, and should be more likely to move. This pattern is supported in the data. Relative to their siblings no longer residing in their birth state at 16, children living in their birth state are 10–15 percentage points less likely to move away from that state as an adult (Table 5).[27] More work is needed to explore the existence of birth-state identity and the extent to which it causally restricts mobility.[28] Unfortunately, these topics are not frequently

[27]The pattern still holds when controlling for whether or not the mother ever lived in the child's 16-year-old state while the child was an adult. If I also control for the share of the child's first 16 years they lived in their birth state, the coefficient on residing in one's birth state at age 16 is almost the same but imprecisely estimated. This might suggest that it is the state a child spends his or her formative years in that matters, not just the place in which that child was born.

[28]Another potential mechanism for "home bias" would be the in-state preference among public universi-

measured in administrative data or large-scale surveys.

6 Impact of State-Border Discontinuities on Local Labor Market Adjustment to Shocks

Regardless of whether the reduction in mobility is due to state identity or some other factor, it is unclear if this empirical pattern has real impacts. Migration flows are an important mechanism for labor markets to adjust to local shocks (Blanchard and Katz, 1992), and reducing migration frictions in general (not border specific) can increase global productivity and welfare (Desmet et al., 2018). Reduced mobility between neighboring counties on state borders might inhibit the rate at which labor markets adjust. This could lead to long-run differences in local economic conditions across geography.

In recent work, Hershbein and Stuart (2020) use event study methods to explore the employment dynamics of local labor markets after recessions in the U.S.[29] They find that places that experienced larger employment declines during the 2007–2009 recession see persistently lower levels of employment up to 10 years later.

Building on their framework, I estimate a similar event study framework but allow the dynamics of border and nonborder counties to differ. Because of the state border, migration to and from neighboring counties will be more constrained in border counties than in nonborder counties. I estimate this as follows:

$$ln(Y_{ct}) = \sum_{\tau=2003}^{2017} \gamma_\tau(CZ\ shock*Year\ \tau) + \theta_\tau(Border*Year\ \tau) + \beta_\tau(Border*CZ\ shock*Year\ \tau) + \delta_c + \alpha_t + \varepsilon_{ct} \quad (14)$$

The outcome of interest is the natural log of total employment, the employment-to-population ratio, migration rates (in and out), and commute rates (in and out) in county c in year t.

ties. In Appendix Figure A27, I test to see whether cross-state migration is different in origin states where the share of public university enrollment that comes from within state is above the median from origin states where it is below the median. This does not appear to affect the drop in migration across state borders. Having a university in the state with students enrolled from nearly all of the states (45) also does not appear to explain the drop in cross-state migration, although the estimates are less precise here.

[29]Since treatment starts at the same time, this approach does not face many of the challenges highlighted for event studies with staggered treatment timing (Callaway and Sant'Anna, 2020; de Chaisemartin and D'Haultfœuille, 2020; Goodman-Bacon, 2021; Sun and Abraham, 2020).

This is regressed on a set of year fixed effects interacted with *CZ shock*, the size of the recession in the local labor market (commuting zone), measured as the change in commuting zone log employment between 2007 and 2009. The commuting zone is used to measure the shock so that counties in the same commuting zone experience the same treatment. Following Hershbein and Stuart (2020), 2005 is used as the omitted year.[30] I also include two more sets of interactions. The border-by-year interactions capture differential time trends between border and interior counties, while the border-by-year-by-size-of-the-shock interactions allow the dynamic effect of the shock to deviate for counties on the state border ($Border = 1$). The dynamic effects for nonborder counties are represented by the γ_τ coefficients, while the dynamic effects of the shock for border counties are represented by $\gamma_\tau + \beta_\tau$. County and state by year fixed effects are also included. Standard errors are corrected for clustering at the level at which the recession shock is measured, the commuting zone. Event study plots are presented in Figure 11.

For both border and non-border counties, prerecession trends are flat, and recessions lead to a large, persistent decrease in employment and in the employment-to-population ratio. However, in border counties, both employment and the employment-to-population ratio are persistently lower, and there is very little recovery up to 10 years after the shock. These gaps are large, even 10 years later the employment levels in border counties remain 40 percent lower than employment in nonborder counties in the same state which experienced the same-sized cyclical shock. Year-to-year effects are only significantly different between border and nonborder counties in the later years, but outcomes from 2008 on are jointly significantly different. A 10 percent drop in local employment during the great recession is associated with approximately 5 percent lower employment in 2017 in nonborder counties, but with an effect nearly twice that size (9.1 percent) in border counties. In short, border counties have experienced little to no employment recovery 10 years after the start of the Great Recession.

[30]Results are similar if I control for the 2005 outcome rather than the county fixed effect, as suggested by Hershbein and Stuart (2020) (see Appendix Figure A28). Because the shock is constructed at the commuting zone rather than the county level, the mechanical relationship between the "treatment" and the outcome is broken.

Consistent with state borders influencing mobility, this appears to be driven by differences in in-migration and in-commuting. After a 10 percent drop in employment during the recession, in-migration to border counties is nearly 4 percent lower than in nonborder counties for the first 6 years of recovery after the end of the recession. In-commuting to border counties is also around 4 percent lower during the recovery through the end of the sample in 2017. Out-migration and out-commuting from border counties is also lower, but not significantly different. This pattern is consistent with prior work, showing that in-migration is more responsive to local economic shocks (Monras, 2018), but appears to be amplified in border counties, where the border imposes an additional friction on mobility.[31]

Being a border county and experiencing less migration from neighboring counties leads to less labor market recovery after a recession, and more persistent negative impacts. Regardless of the mechanism behind the state-border discontinuity in migration, this empirical pattern has large and lasting impacts on labor market dynamism.[32]

7 Conclusion

I present new evidence that both residential and employment county-to-county mobility in the U.S. falls discontinuously across state borders. The drop in cross-state migration is large (a 60–70 percent reduction for close counties), persists when examining border counties or counties in the same labor market, and is not confined to particular demographic groups. Using the theoretical migration choice model to infer potential causes of this pattern, I find that differences in local characteristics which could differentially impact utility do not drive

[31]Consistent with the drop in in-migration, total population also falls more in border counties, although the difference is not significant. The impacts on employment would suggest that the employment propensity of in-migrants must be different in border and nonborder counties. County border status does not appear to have differential impacts on average weekly wages.

[32]For reference, state border status leads to a similar decline in employment recovery as national border status, but unlike counties on the national border, the gap in employment and employment-to-population ratios does not close by 2017 (Appendix Figure A30). For completeness, I also examine the employment response to positive local economics shocks in the form of fracking booms. In this setting, employment in border counties appears to grow more slowly, but the difference is not significant: in-commuting to border counties is actually higher. (Appendix Figure A31).

the difference. Occupational licensing and state income taxation, as well as state welfare generosity, do not appear to drive the gap. Other pecuniary adjustment costs are unlikely to be the sole driving force, as county-to-county commuting, a form of temporary, repeated mobility, follows a similar pattern.

County-to-county connectedness plays a potentially important role. Facebook friend networks exhibit a similar drop across state borders, and controlling for the Facebook network drastically mitigates the cross-state mobility gap. This empirical pattern is consistent with either psychic costs, information frictions, or home bias driving the relationship. Patterns in the data are most consistent with home bias, or state identity, reducing people's willingness to move out of their home state. The data provide less evidence that a lack of social connections or information that might be transferred through social networks is causing mobility to drop across state borders.

This empirical pattern has real economic impacts. Border counties see lower in-migration and in-commuting after local economic shocks, and persistently lower employment levels. This sheds new light on how we should view and evaluate geographic differences in labor market dynamism. Future work is needed to better pinpoint two aspects: 1) the role of behavioral biases, like home bias or state identity, in reducing mobility across state borders, and 2) whether there are policy tools that can mitigate or offset the economic impact of this feature of migration behavior.

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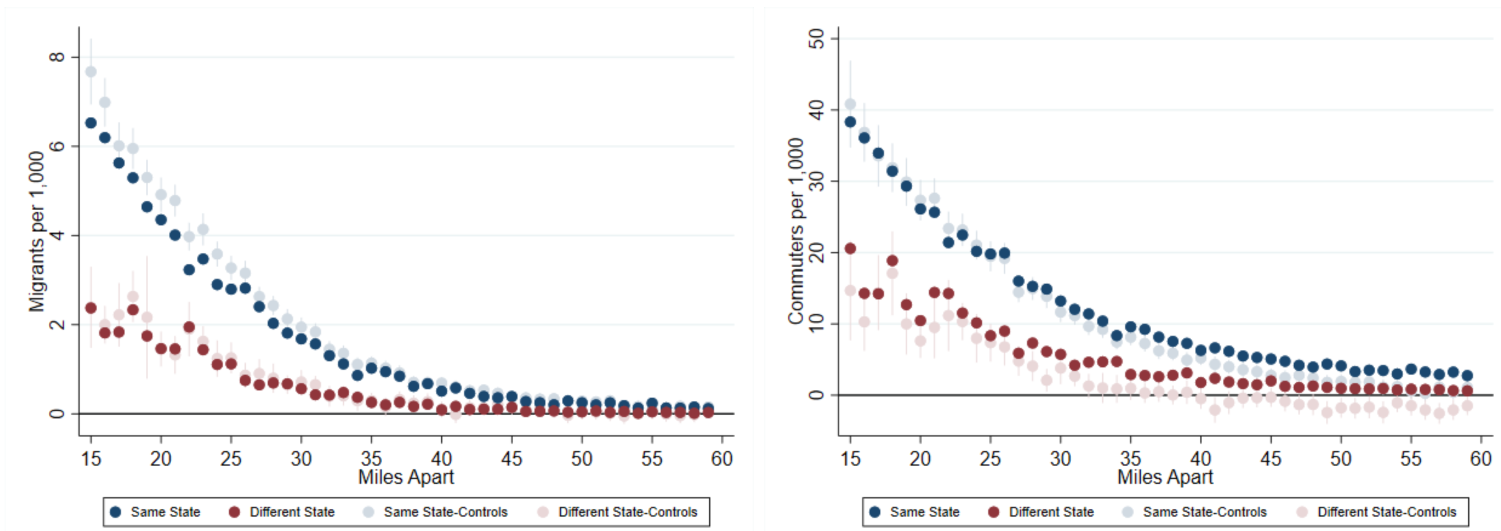
Tables and Figures

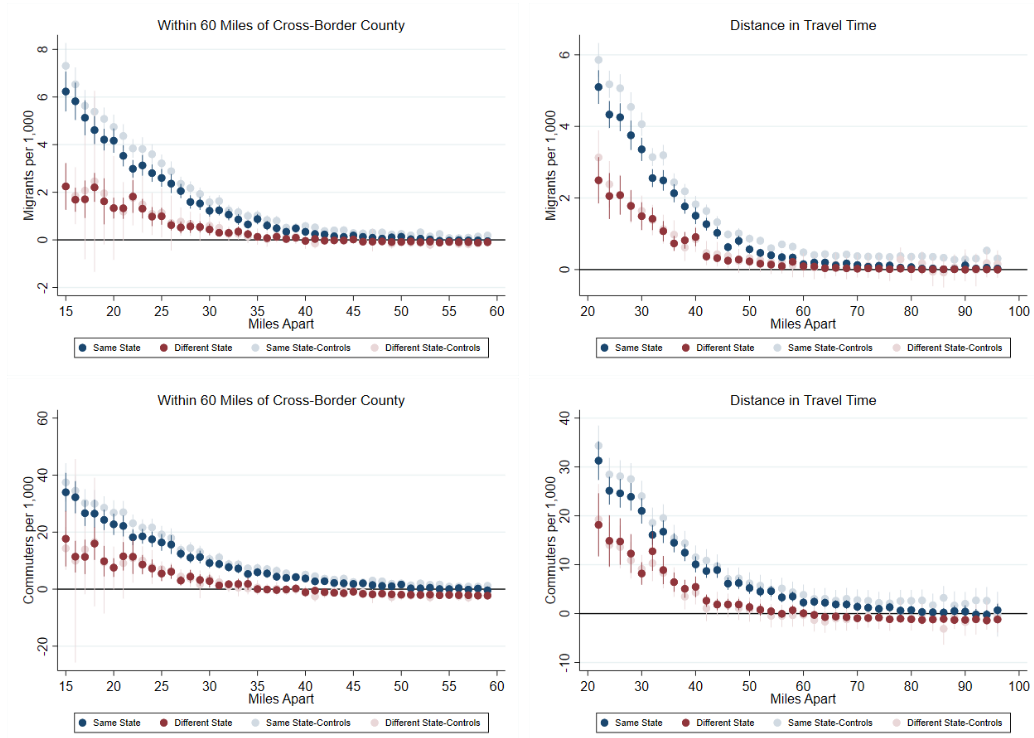
Figure 1: County-to-County Migration and Commute Rates by Distance for Same-State and Different-State County Pairs



NOTE: Outcome in the left panel is number of migrants per 1,000 people at the origin county using the IRS SOI county-to-county flows from 2017. Outcome in the right panel is the number of commuters per 1,000 people at the origin county using the LODES origin-destination employment statistics aggregated to the county level from 2017. These measures are then averaged into one-mile bins for county pairs in the same state and county pairs in different states. Distance is the distance between the population-weighted county centroids. "With Controls" plots coefficients from Equation (2), accounting for origin fixed effects, destination fixed effects, and differences between the origin and destination county in labor market measures (the unemployment rate, employment-to-population ratio, average weekly wages, number of establishments), differences in industry shares (share of natural resources and mining, construction, manufacturing, trade, information, finance, professional, education and health, hospitality, public sector, and all others), differences in demographics (total population, share female, non-Hispanic White, non-Hispanic Black, non-Hispanic other, Hispanic, under 20, 20–34, 35–49, 50–64, and 65 and older), differences in natural amenities (the January average temperature, January average sunlight, July average temperature, July average humidity, and the USDA natural amenities scale), the 2016 presidential Republican vote share, differences in the county housing price index converted to dollars using the median house value from 2000, and differences in average third- through eighth-grade math and reading language arts test scores. Ninety-five-percent confidence intervals are provided.

SOURCE: Author's own calculations using the 2017 IRS SOI and 2017 LODES.

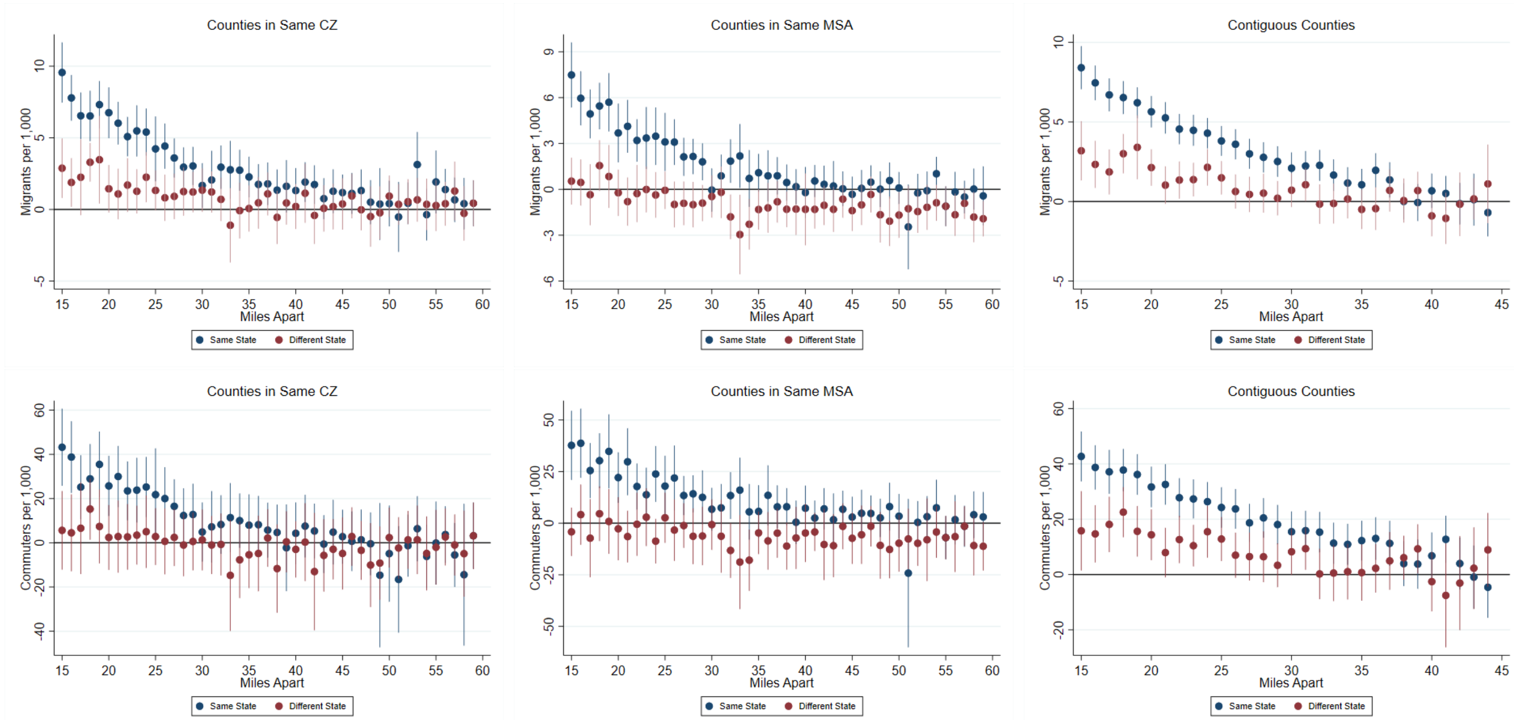
Figure 2: Sensitivity of Migration and Commuting across State Borders



NOTE: Coefficients from Equation (1) are plotted. Migration is plotted in the top panel, commuting in the bottom. The left panel restricts the sample to only include counties within 60 miles of a county in a different state. The right panel only includes counties within 60 miles of a county in a different state, but distance is the number of minutes of travel time between the population-weighted county centroids. "With Controls" plots coefficients from Equation (2), accounting for origin fixed effects, destination fixed effects, and differences between the origin and destination county in labor market measures (the unemployment rate, employment-to-population ratio, average weekly wages, number of establishments), differences in industry shares (share in natural resources and mining, construction, manufacturing, trade, information, finance, professional, education and health, hospitality, public sector, and all others), differences in demographics (total population, share female, non-Hispanic White, non-Hispanic Black, non-Hispanic other, Hispanic, under 20, 20–34, 35–49, 50–64, and 65 and older), differences in natural amenities (the January average temperature, January average sunlight, July average temperature, July average humidity, and the USDA natural amenities scale), the 2016 presidential Republican vote share, differences in the county housing price index converted to dollars using the median house value from 2000, and differences in average third- through eighth-grade math and reading language arts test scores. Ninety-five-percent confidence intervals are provided.

SOURCE: Author's own calculations using the 2017 IRS SOI and 2017 LODES.

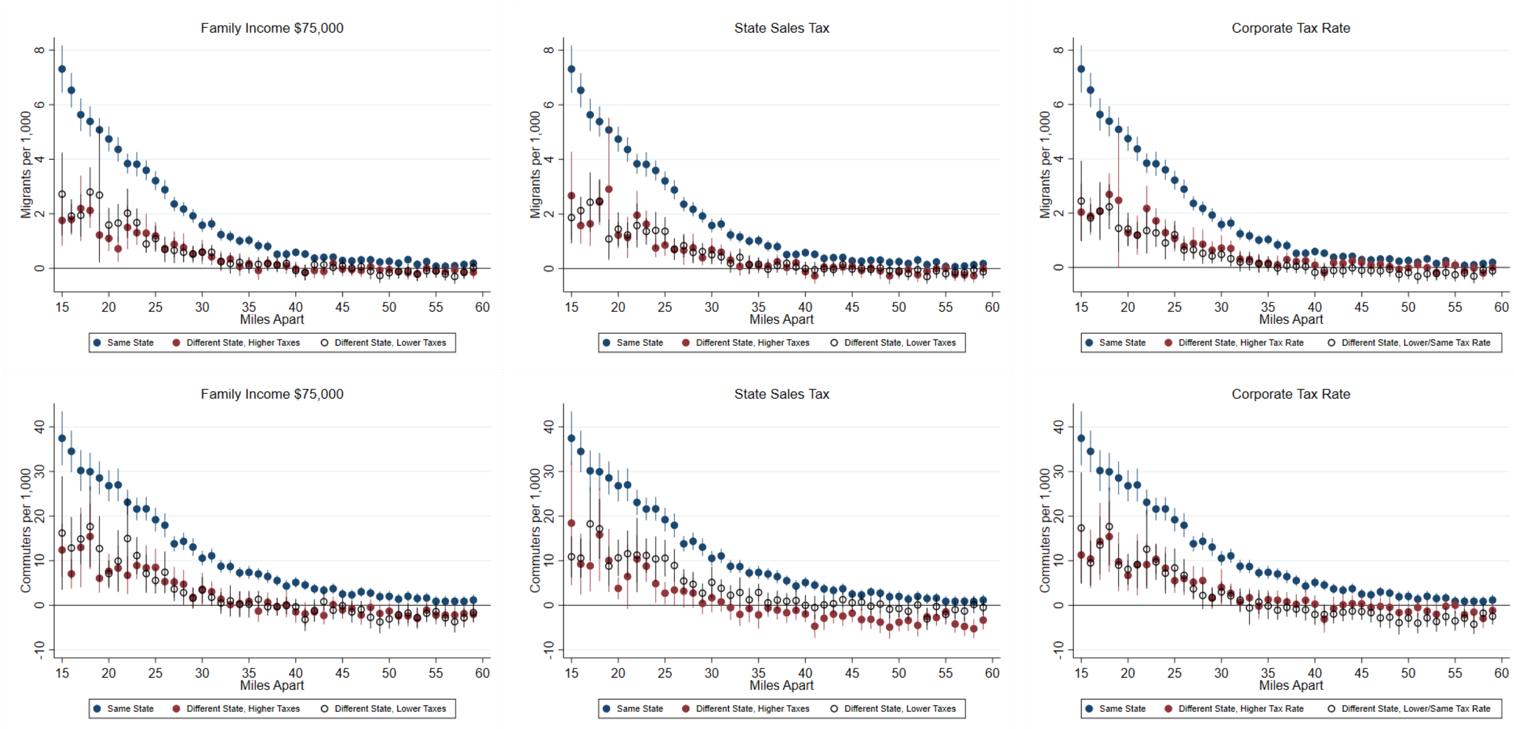
Figure 3: Impact of State Borders on Migration and Commuting in Close, Connected Regions



NOTE: Coefficients from Equation (2) are plotted. Migration is plotted in the top panel, commuting in the bottom. The left panel restricts the sample to include only counties in commuting zones (CZ) that cross state borders and to include only county pairs that are in the same CZ. The middle panel includes only counties in MSAs that cross state borders and includes only county pairs that are in the same MSA. The right panel includes only counties that are on state borders and are contiguous. Estimation controls for origin fixed effects, destination fixed effects, and differences between the origin and destination county in labor market measures (the unemployment rate, employment-to-population ratio, average weekly wages, number of establishments), differences in industry shares (share in natural resources and mining, construction, manufacturing, trade, information, finance, professional, education and health, hospitality, public sector, and all others), differences in demographics (total population, share female, non-Hispanic White, non-Hispanic Black, non-Hispanic other, Hispanic, under 20, 20–34, 35–49, 50–64, and 65 and older) differences in natural amenities (the January average temperature, January average sunlight, July average temperature, July average humidity, and the USDA natural amenities scale), the 2016 presidential Republican vote share, differences in the county housing price index, converted to dollars using the median house value from 2000, and differences in average third- through eighth-grade math and reading language arts test scores. Ninety-five-percent confidence intervals are provided.

SOURCE: Author's own calculations using the 2017 IRS SOI and 2017 LODES.

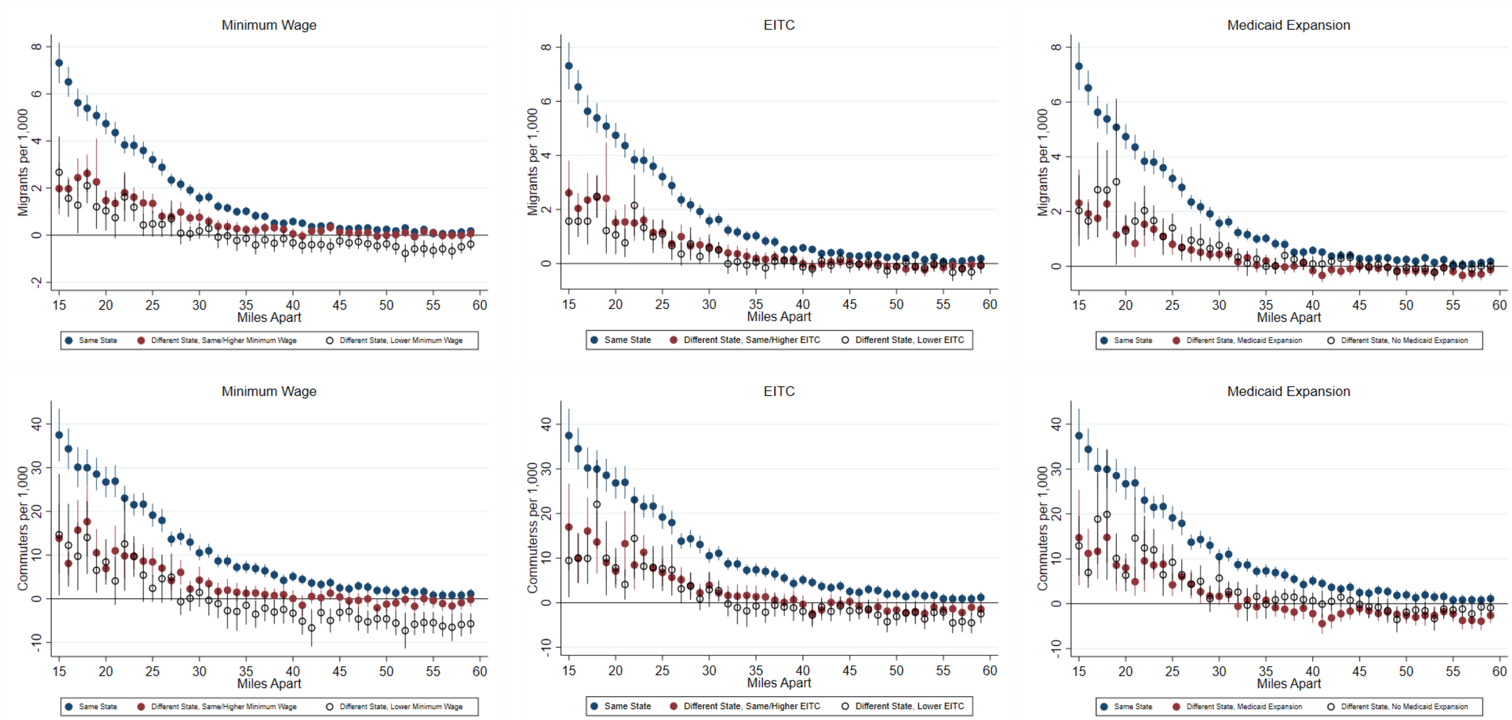
Figure 4: Role of State Taxation: Migration and Commuting across State Borders



NOTE: Coefficients from Equation (6) are plotted. Migration is plotted in the top panel, commuting in the bottom. The left panel plots differences by state+federal income tax burdens for a married household with two dependents with $75,000 annual income. The middle panel plots differences by state sales tax rates. The right panel plots differences by the maximum state corporate tax rate. Controls include origin fixed effects, destination fixed effects, and differences between the origin and destination county in labor market measures (the unemployment rate, employment-to-population ratio, average weekly wages, number of establishments), differences in industry shares (share in natural resources and mining, construction, manufacturing, trade, information, finance, professional, education and health, hospitality, public sector, and all others), differences in demographics (total population, share female, non-Hispanic White, non-Hispanic Black, non-Hispanic other, Hispanic, under 20, 20–34, 35–49, 50–64, and 65 and older) differences in natural amenities (the January average temperature, January average sunlight, July average temperature, July average humidity, and the USDA natural amenities scale), the 2016 presidential Republican vote share, differences in the county housing price index, converted to dollars using the median house value from 2000, and differences in average third- through eighth-grade math and reading language arts test scores. Ninety-five-percent confidence intervals are provided.

SOURCE: Author's own calculations using the 2017 IRS SOI and 2017 LODES.

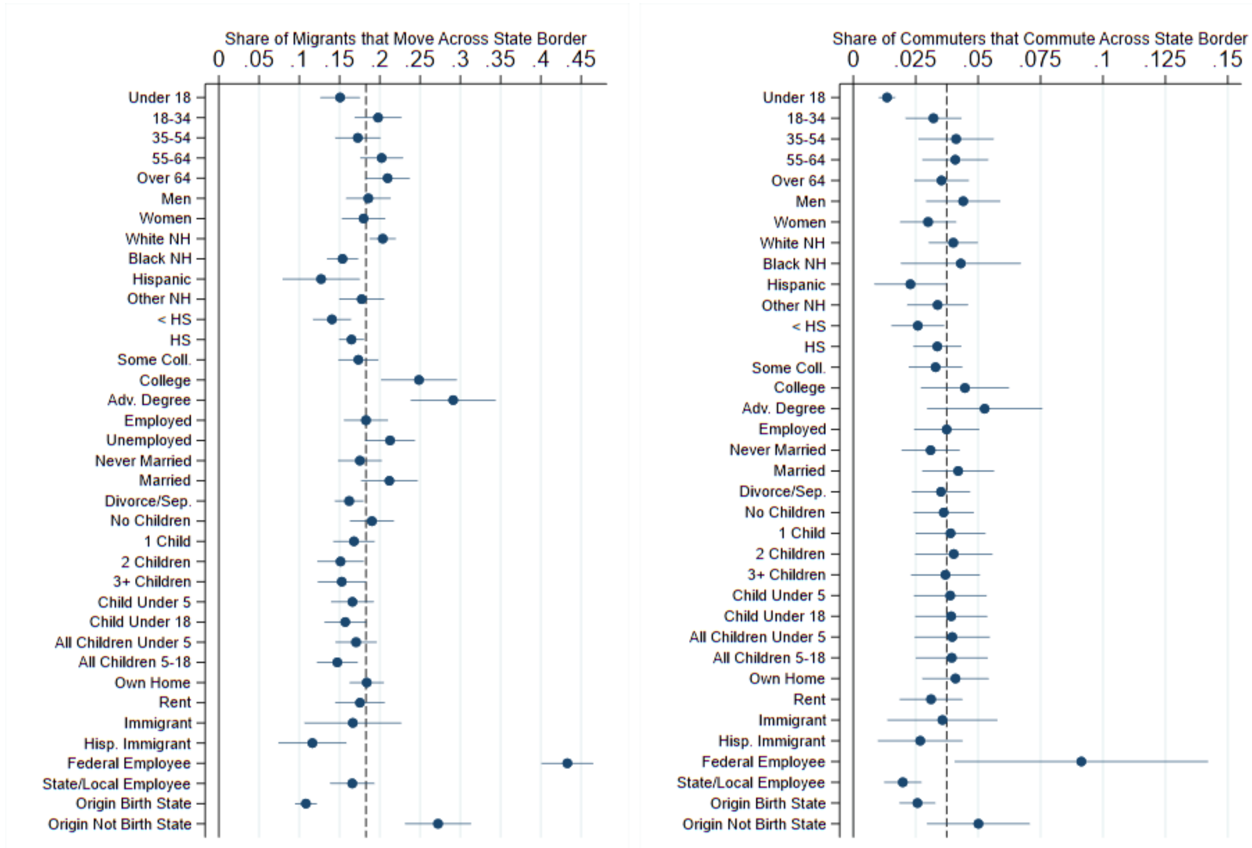
Figure 5: Role of State Benefits and Welfare: Migration and Commuting across State Borders



NOTE: Coefficients from Equation (6) are plotted. Migration is plotted in the top panel, commuting in the bottom. The left panel plots differences by the prevailing minimum wage. The middle panel plots differences by generosity of the state EITC. The right panel plots differences by whether the state expanded Medicaid after the Affordable Care Act. Controls include origin fixed effects, destination fixed effects, and differences between the origin and destination county in labor market measures (the unemployment rate, employment-to-population ratio, average weekly wages, number of establishments), differences in industry shares (share in natural resources and mining, construction, manufacturing, trade, information, finance, professional, education and health, hospitality, public sector, and all others), differences in demographics (total population, share female, non-Hispanic White, non-Hispanic Black, non-Hispanic other, Hispanic, under 20, 20–34, 35–49, 50–64, and 65 and older) differences in natural amenities (the January average temperature, January average sunlight, July average temperature, July average humidity, and the USDA natural amenities scale), the 2016 presidential Republican vote share, differences in the county housing price index converted to dollars using the median house value from 2000, and differences in average third- through eighth-grade math and reading language arts test scores. Ninety-five-percent confidence intervals are provided.

SOURCE: Author's own calculations using the 2017 IRS SOI and 2017 LODES.

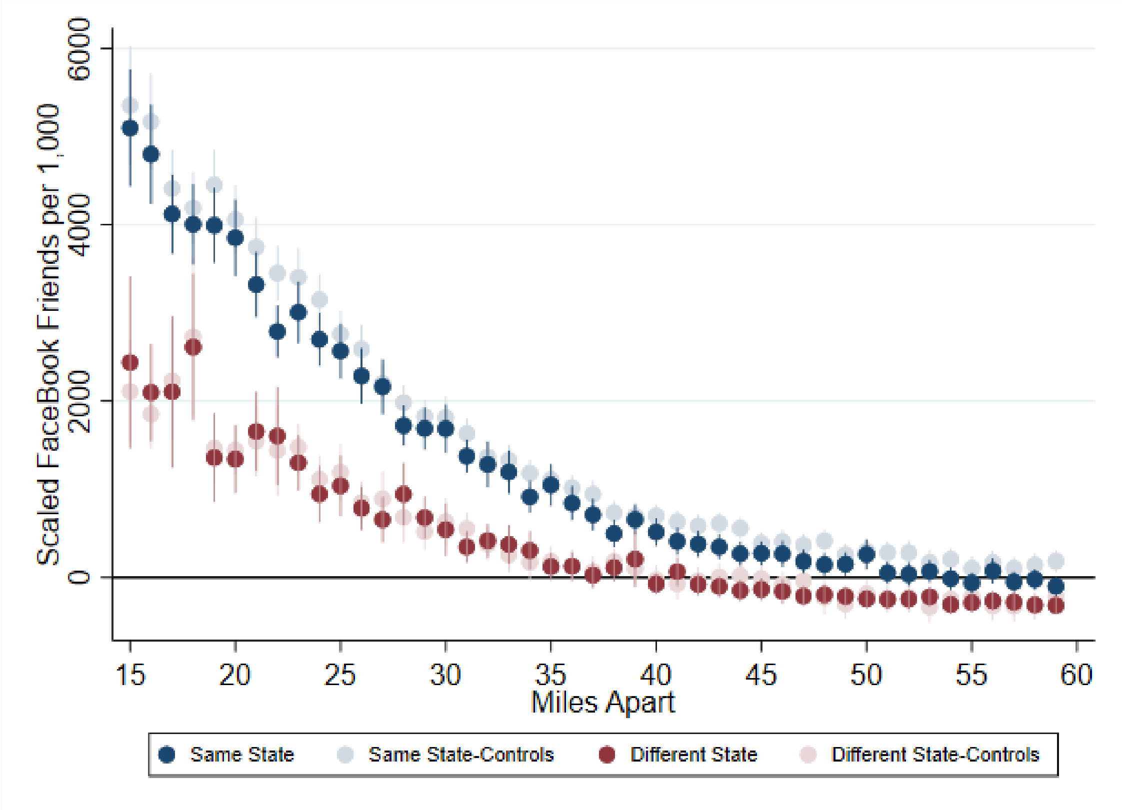
Figure 6: Role of Demographics: Cross-State Migration and Commuting across Demographic Groups in the ACS



NOTE: Each point represents the share of migrants that moved across state borders within the past year using the 2012–2017 ACS (left) or the share of commuters who travel across state lines when they commute using the 2012–2017 ACS (right).

SOURCE: Author's own calculations using the 2012–2017 ACS.

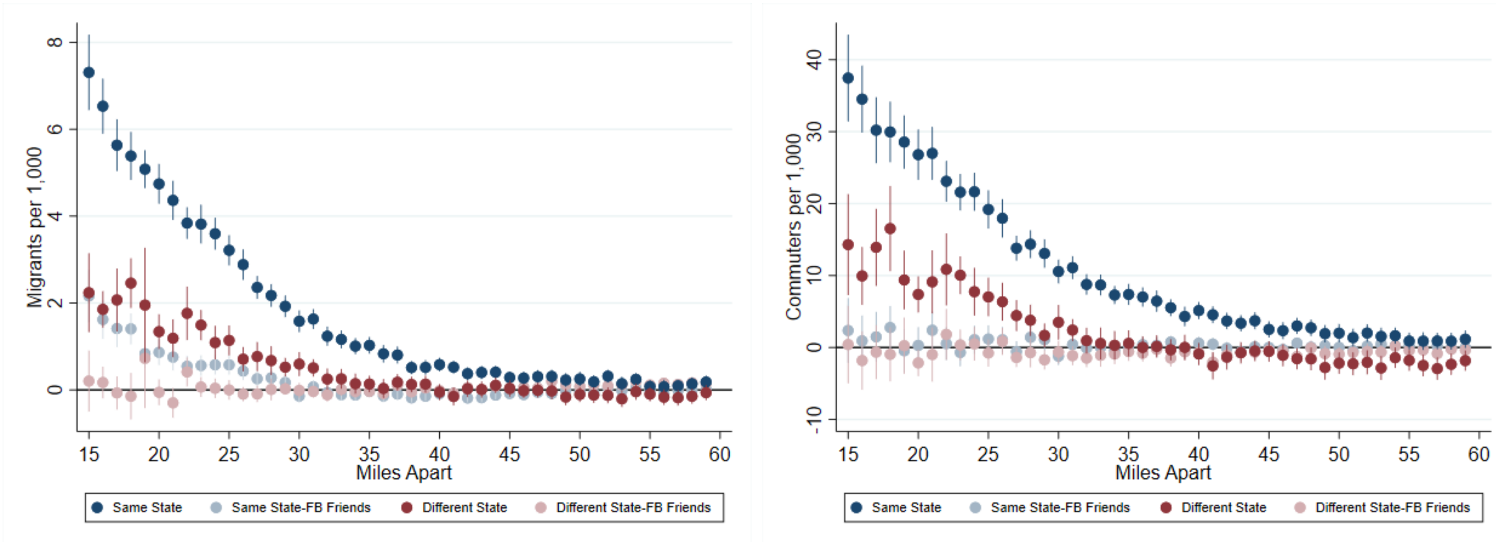
Figure 7: Impact of State Borders on County-to-County Facebook Friendship Rates



NOTE: Coefficients from Equations (1) and (2) are plotted where the outcome is the number of Facebook friends of residents in the destination county per person in the origin county in 2000 using the SCI. The number of Facebook friends is scaled by an unknown constant, for privacy. Ninety-five-percent confidence intervals are included.

SOURCE: Author's own calculations using the 2016 SCI and 2017 IRS SOI.

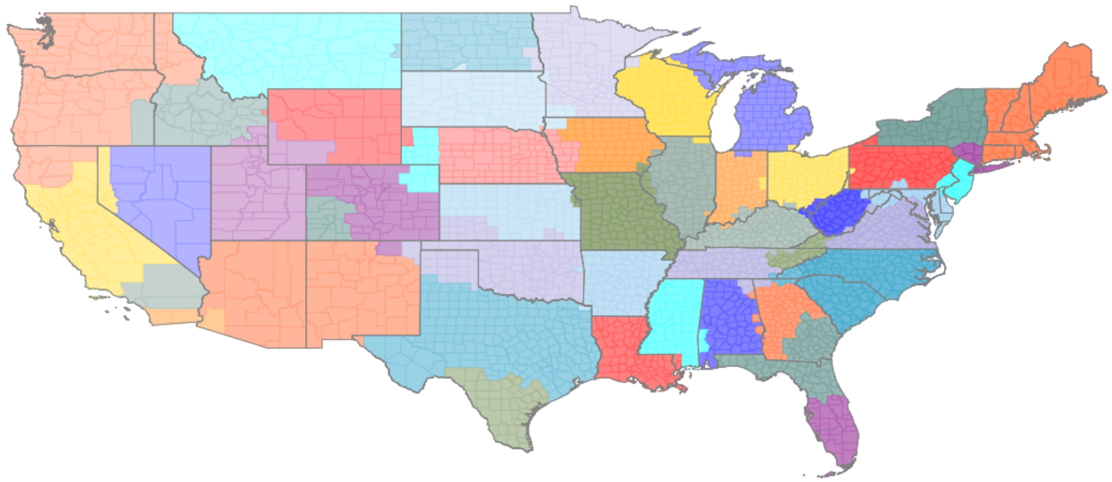
Figure 8: Mediating Role of Facebook network on Migration and Commuting across State Borders



NOTE: Coefficients from Equation (2) are plotted, where the outcome is the migration rate (left) or the commute rate (right), and when we also control for the county-to-county Facebook friendship rate. Ninety-five-percent confidence intervals are included.

SOURCE: Author's own calculations using the 2016 SCI, 2017 IRS SOI, and 2017 LODES.

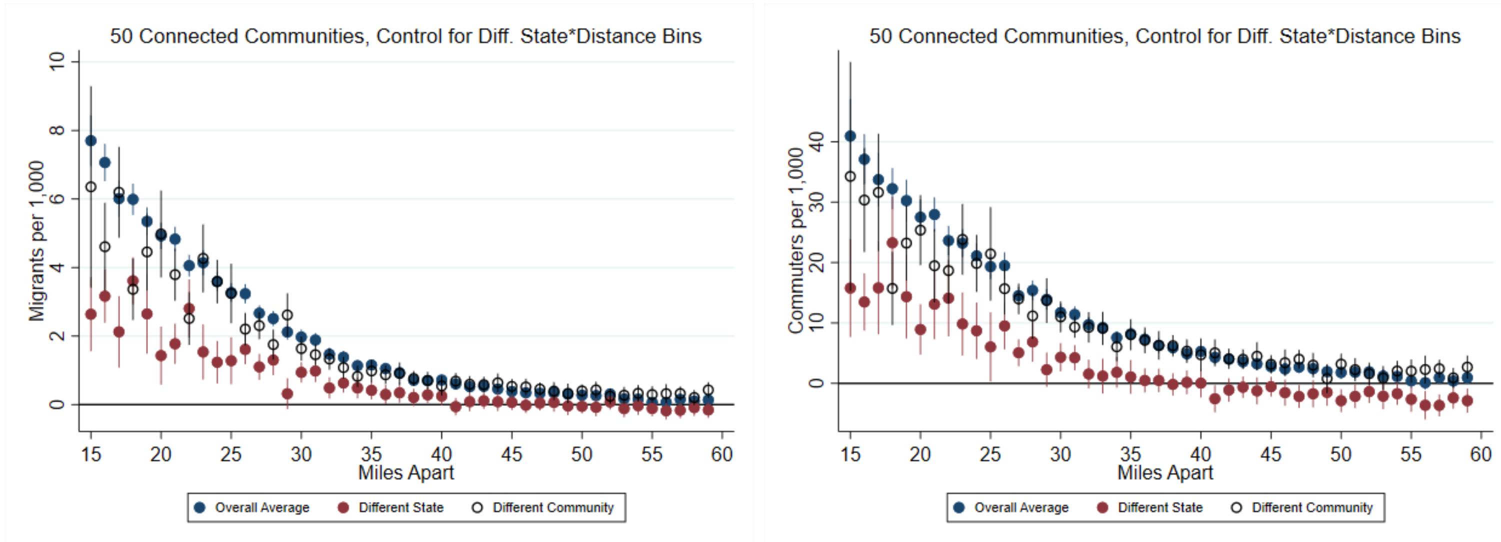
Figure 9: Connected Community Clusters Based on Facebook Friendship Links, 50 Communities



NOTE: Connected Community boundaries plotted when there are 50 connected community clusters. These clusters capture contiguous counties and cover the entire country.

SOURCE: Author's own calculations using the 2016 SCI.

Figure 10: Horserace Regression: Relative Importance of Physical State Borders versus Pseudo Connected Community Borders



NOTE: Sample restricted to counties that are less than 60 miles from another county in a different state. The outcomes are migration rates (left) and commuting rates (right). Each panel plots the coefficients from Equation (2) but includes the full set of state-border-by-distance interactions and the connected-community-border-by-distance interactions. Ninety-five-percent confidence intervals are provided.

SOURCE: Author's own calculations using the 2016 SCI, 2017 IRS SOI, and 2017 LODES.

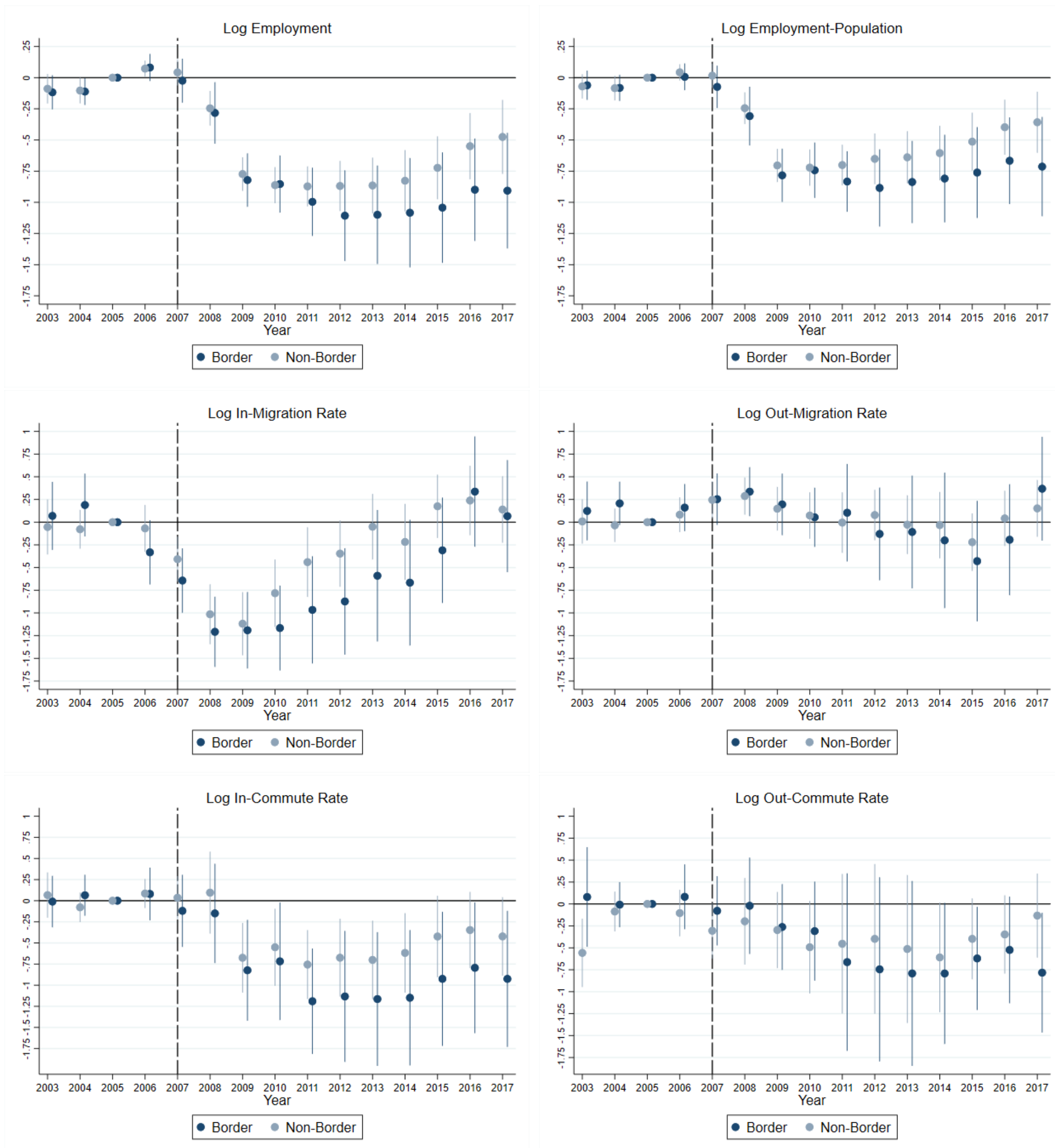


Figure 11: Impact of State Borders on Labor Market Recovery after the Great Recession

NOTE: Event study coefficients from Equation (14) are plotted with 95 percent confidence intervals and represent the percent change in outcomes relative to 2005 for each percentage point increase in commuting zone employment reduction between 2007 and 2009. Observation at the county by year level. County, state-by-year fixed effects, as well as an indicator for being a border county interacted with year fixed effects, are included. Standard errors corrected for clustering at the commuting zone level.

SOURCE: Author's own calculations using the 2000–2017 QCEW and 2000–2017 IRS SOI, and 2003-2017 LODES.

Table 1: Impact of State Occupational Licenses on Cross-State Migration, ACS Microdata

	Sample: All Individuals Move Out of State in Last Year			Sample: All Movers Move Out of State in Last Year			All Commuters Commute Out of State		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	More Restrictive Measure of Occupational Licensing								
Licensed Occupation	0.001	0.001	0.001	0.004	0.003	0.003	0.001	0.001	0.001
	(0.002)	(0.002)	(0.002)	(0.013)	(0.012)	(0.013)	(0.003)	(0.001)	(0.001)
Occupation F.E.	X	X	X	X	X	X	X	X	X
State and Year F.E.		X	X		X	X		X	X
Occupation by Year F.E.			X			X			X
Dependent Mean	0.023	0.023	0.023	0.169	0.169	0.169	0.039	0.039	0.039
Observations	9,493,532	9,493,532	9,493,532	1,271,370	1,271,370	1,271,370	4,300,760	4,300,760	4,300,760
	Less Restrictive Measure of Occupational Licensing								
Licensed Occupation	0.001	0.001	0.001	0.000	0.001	0.001	-0.003*	-0.001	-0.001
	(0.002)	(0.002)	(0.002)	(0.010)	(0.010)	(0.010)	(0.002)	(0.001)	(0.001)
Occupation F.E.	X	X	X	X	X	X	X	X	X
State and Year F.E.		X	X		X	X		X	X
Occupation by Year F.E.			X			X			X
Dependent Mean	0.023	0.023	0.023	0.169	0.169	0.169	0.039	0.039	0.039
Observations	9,493,532	9,493,532	9,493,532	1,271,370	1,271,370	1,271,370	4,300,760	4,300,760	4,300,760

NOTE: Sample restricted to adult respondents to the 2015–2017 ACS. State occupational licensing measures constructed from the Current Population Survey(CPS) questions on job certification. From 2015 on, CPS respondents have been asked if they have a professional certificate or license; if the license was issued by the federal, state, or local government; and if the government-issued license is required for their job. I then construct the share of adults in state-by-year-by-four-digit occupation bins that report having a government-issued license. As (Kleiner and Soltas, 2019) report, occupational licensing in the CPS is measured with error. Even universal licensed occupations have licensure rates below 100 percent. To indicate the presence of a license, I indicate whether the fraction of adults in the state, year, occupation bin that report a government license is over a given threshold. In the top panel, the threshold is 25 percent. In the bottom panel, the threshold is 10 percent. For migration outcomes, fixed effects for state of residence one year ago are included in columns (2) and (4). For commuting, fixed effects for the current state of residence are included in column (6). Standard errors corrected for clustering at the state level (state of residence in previous year for migration, current state for commuting). $p < 0.1$ = *; $p < 0.05$ = **; $p < 0.01$ = ***.

Table 2: Relationship between Birth State Residence and Migration

			Among Movers				Among Commuters	
	Move at All		Move Out of PUMA, Stay in State		Move Out of State		Commute Out of State	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Originally in Birth State	-0.013***	-0.035***	0.048***	0.052***	-0.152***	-0.157***		
	(0.002)	(0.001)	(0.002)	(0.002)	(0.004)	(0.003)		
Currently in Birth State							-0.019***	-0.017***
							(0.002)	(0.001)
Demographic Controls		X		X		X		X
Dependent Mean, Not Birth State	0.15	0.15	0.16	0.16	0.24	0.24	0.05	0.05
Observations	18,871,967	18,871,967	2,537,353	2,537,352	2,537,353	2,537,352	8,426,384	8,426,383

NOTE: Sample restricted to adult respondents to the 2012–2017 ACS. Estimates obtained by regressing Equation (7). For migration outcomes, PUMA by state of residence one year ago fixed effects are included in columns. For commuting, PUMA by current state of residence fixed effects are included. Standard errors corrected for clustering at the state-by-PUMA level (previous year's state for migration, current year's state for commuting). $p < 0.1$ = *; $p < 0.05$ = **; $p < 0.01$ = ***.

Table 3: Heterogeneous Impact of State Border on Mobility by Strength of State Identity, Gallup Survey

	Migrants per 1,000		Commuters per 1,000	
	(1)	(2)	(3)	(4)
Diff. State	-0.602***	0.088	-5.315***	-3.138***
	(0.030)	(0.121)	(0.228)	(0.783)
Diff. State*Share Feel State is the Best		-8.987***		-28.353***
		(0.121)		(0.783)
Dependent Mean	1.15	1.15	8.98	8.98
Observations	35,242	35,214	35,242	35,214

NOTE: Observation at the origin/destination county pair level, using the IRS SOI 2017 data. *Diff. State* is an indicator for whether the counties are in different states. *Share Feel State is "the Best"* is obtained from a 2013 Gallup survey on own-state preferences and measured at the state level. All regressions include one-mile-distance bin fixed effects, origin fixed effects, destination fixed effects, and differences between the origin and destination county in labor market measures (the unemployment rate, employment-to-population ratio, average weekly wages, number of establishments), differences in industry shares (share in natural resources and mining, construction, manufacturing, trade, information, finance, professional, education and health, hospitality, public sector, and all others), differences in demographics (total population, share female, non-Hispanic White, non-Hispanic Black, non-Hispanic other, Hispanic, under 20, 20–34, 35–49, 50–64, and 65 and older) differences in natural amenities (the January average temperature, January average sunlight, July average temperature, July average humidity, and the USDA natural amenities scale), the 2016 presidential Republican vote share, differences in the county housing price index converted to dollars using the median house value from 2000, and differences in average third- through eighth-grade math and reading language arts test scores. Distance is the distance between the population-weighted county centroids. Standard errors are corrected for clustering at the origin county level. $p < 0.1$ = *; $p < 0.05$ = **; $p < 0.01$ = ***.

Table 4: Relationship between Birth State Identity and Migration, Pew Mobility Survey

	Ever Left Birth State		Birth State Preferred		Likely Move in Next 5 Years		Would Move to One of MSA Provided	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Birth State Identity	-0.353***	-0.328***	0.281***	0.268***	-0.019	-0.011	0.043	0.045
	(0.021)	(0.022)	(0.027)	(0.026)	(0.037)	(0.038)	(0.027)	(0.027)
Birth State Identity*In Birth State					-0.131**	-0.123**	-0.084**	-0.090**
					(0.055)	(0.057)	(0.041)	(0.041)
Family Ties		-0.143***		0.072***		-0.073**		-0.024
		(0.025)		(0.021)		(0.035)		(0.028)
Family Ties*In Birth State						-0.001		0.037
						(0.046)		(0.035)
Amenity Ties		0.019		-0.005		0.063		0.075*
		(0.028)		(0.025)		(0.043)		(0.038)
Amenity Ties*In Birth State						-0.112**		-0.063
						(0.055)		(0.046)
In Birth State					0.019	0.118*	0.008	0.045
					(0.055)	(0.063)	(0.031)	(0.055)
Dependent Mean	0.555	0.555	0.351	0.351	0.370	0.370	0.781	0.781
Observations	1,948	1,948	1,949	1,949	1,948	1,948	1,948	1,948

NOTE: Sample restricted to U.S.-born survey respondents from the 2008 Pew Research Center Mobility Survey. Regression controls for sex, education level, race, ethnicity, age and age squared, as well as current state of residence fixed effects. Observations are weighted using the Pew Research Center survey weights. Standard errors corrected for clustering at the current state of residence level. $p < 0.1$ = *; $p < 0.05$ = **; $p < 0.01$ = ***.

Table 5: Propensity to Move Out-of-State if Living in Birth State at 16, PSID Sibling Comparison

	Moved from State Lived in at 16-Years-Old							
	Between Ages 18-30				Between Ages 18-40			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
In Birth State at 16	-0.067	-0.096**	-0.104**	-0.094	-0.131**	-0.146**	-0.150**	-0.127
	(0.042)	(0.046)	(0.045)	(0.078)	(0.056)	(0.067)	(0.068)	(0.110)
Mother Present in 16-Year-Old State During Time Period			-0.303***	-0.304***			-0.304***	-0.304***
			(0.069)	(0.069)			(0.114)	(0.114)
Share of First 16 Years in Birth State				-0.016				-0.043
				(0.096)				(0.133)
Birth State and Cohort F.E.		X	X	X		X	X	X
Mother F.E.	X	X	X	X	X	X	X	X
	Birth Cohorts 1968-1989				Birth Cohorts 1968-1979			
Dependent Mean	0.216	0.216	0.222	0.222	0.240	0.240	0.246	0.246
Observations	5,205	5,205	4,768	4,768	3,258	3,258	3,003	3,003

NOTE: Sample restricted to children of the PSID that were born in 1968 or later, so that state of residence at birth can be established. Outcome variables are indicators for whether the individual has moved from the state that individual lived in at 16 by the specified ages. Only moves in adulthood are included. *In Birth State at 16* indicates whether the child is living in his or her state of birth at age 16. In 1999, the PSID moved to a biannual survey. As such, outcomes at specific ages are not observed for cohorts born later. For this reason, I update variables to go through the specified age plus one for cohorts that are not surveyed when they reach the specified age (e.g., 16, 30, or 40). Samples are restricted to include birth cohorts that reach the maximum age specified in the outcome by 2019, the last available year in the data. Mother fixed effects are included to make this a within-sibling comparison. Birth-cohort fixed effects control for fixed differences in the propensity of moving by birth year, while birth-state fixed effects control for fixed differences in the propensity of moving across birth states. Standard errors corrected for clustering at the mother ID level. $p < 0.1$ = *; $p < 0.05$ = **; $p < 0.01$ = ***.

Appendix Tables and Figures

Table A1: Share of Counties with Labor Market or Housing Conditions Nearby

	Distance Between Origin and Destination			In Different Commuting Zone		
	<30 Miles (1)	<60 Miles (2)	<90 Miles (3)	<30 Miles (4)	<60 Miles (5)	<90 Miles (6)
	Exists County with Unemployment Rate...					
10 Percent Lower	0.54	0.81	0.90	0.30	0.73	0.87
20 Percent Lower	0.31	0.63	0.77	0.17	0.55	0.73
30 Percent Lower	0.13	0.39	0.53	0.07	0.34	0.51
	Exists County with Average Weekly Wages...					
10 Percent Higher	0.53	0.83	0.91	0.28	0.74	0.88
20 Percent Higher	0.36	0.70	0.83	0.16	0.60	0.79
30 Percent Higher	0.22	0.56	0.74	0.09	0.45	0.69
	Exists County with Average House Price...					
10 Percent Lower	0.60	0.85	0.93	0.39	0.80	0.91
20 Percent Lower	0.48	0.75	0.84	0.31	0.69	0.82
30 Percent Lower	0.36	0.60	0.71	0.24	0.56	0.69
	Both Wages and Housing...					
10 Percent Difference	0.25	0.48	0.61	0.13	0.41	0.58
20 Percent Difference	0.12	0.28	0.37	0.06	0.24	0.35
30 Percent Difference	0.05	0.17	0.24	0.03	0.14	0.22

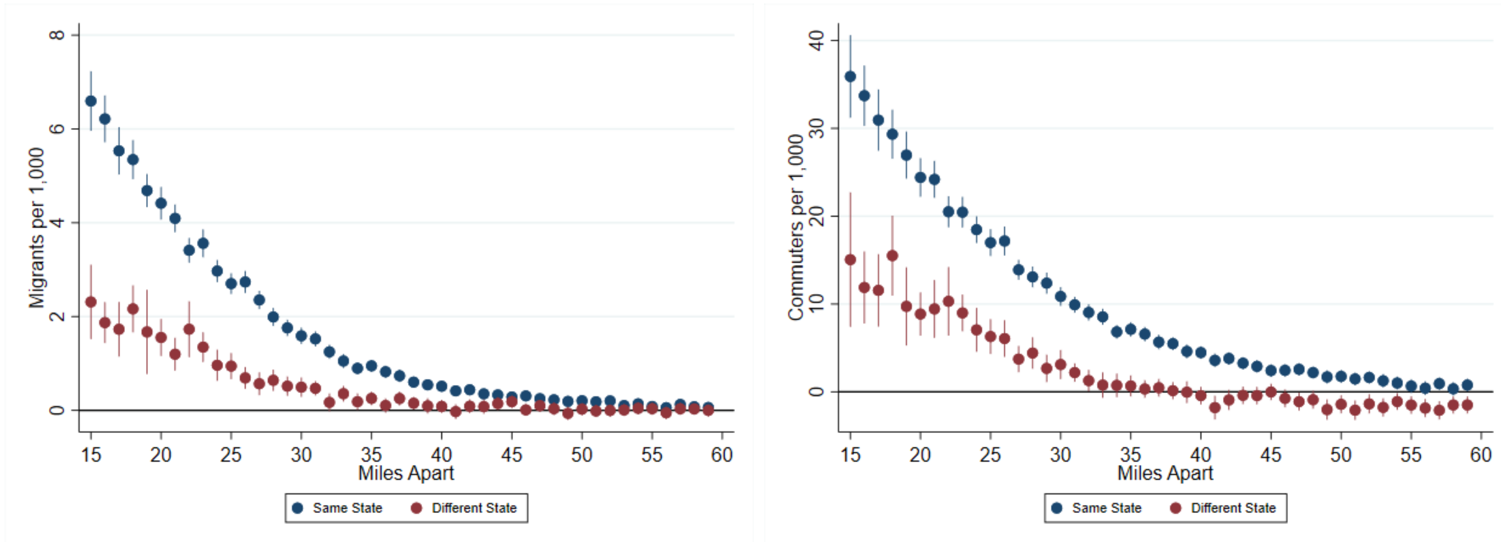
NOTE: Shares reported based on 2017 measures. Unemployment data obtained from the BLS LAUS; "Average Weekly Wages" obtained from the QCEW; "Average House Price" obtained by combining FHFA county house price indices with home values from the 2000 census to estimate 2017 average house prices. "Distance" is the distance between county population centroids. SOURCE: Author's own calculations.

Table A2: Share of Gallup Respondents Who Feel Their State Is the Best Possible State to Live In

State	Share of Respondents Who Feel Their State is the Best Possible State to Live In
TEXAS	0.28
ALASKA	0.27
HAWAII	0.25
MONTANA	0.24
NORTH DAKOTA	0.21
WYOMING	0.21
COLORADO	0.18
UTAH	0.15
WASHINGTON	0.14
VERMONT	0.14
SOUTH DAKOTA	0.13
NEW HAMPSHIRE	0.13
MINNESOTA	0.13
IOWA	0.13
CALIFORNIA	0.13
OREGON	0.13
FLORIDA	0.11
WEST VIRGINIA	0.11
IDAHO	0.11
TENNESSEE	0.10
ARIZONA	0.10
SOUTH CAROLINA	0.10
MAINE	0.10
NEBRASKA	0.10
ALABAMA	0.10
GEORGIA	0.09
NEVADA	0.09
NEW YORK	0.09
KENTUCKY	0.08
WISCONSIN	0.08
ARKANSAS	0.08
VIRGINIA	0.07
LOUISIANA	0.07
OKLAHOMA	0.07
MISSISSIPPI	0.07
DELAWARE	0.07
MASSACHUSETTS	0.07
PENNSYLVANIA	0.06
NEW JERSEY	0.06
INDIANA	0.06
NORTH CAROLINA	0.06
KANSAS	0.05
MICHIGAN	0.05
MARYLAND	0.05
NEW MEXICO	0.05
OHIO	0.04
MISSOURI	0.04
ILLINOIS	0.03
RHODE ISLAND	0.03
CONNECTICUT	0.03

NOTE: Estimates constructed by Gallup, based on a 2013 survey of nearly 600 respondents. Obtained from Gallup at `https://news.gallup.com/poll/168653/montanans-alaskans-say-states-among-top-places-live.aspx?version=print`.

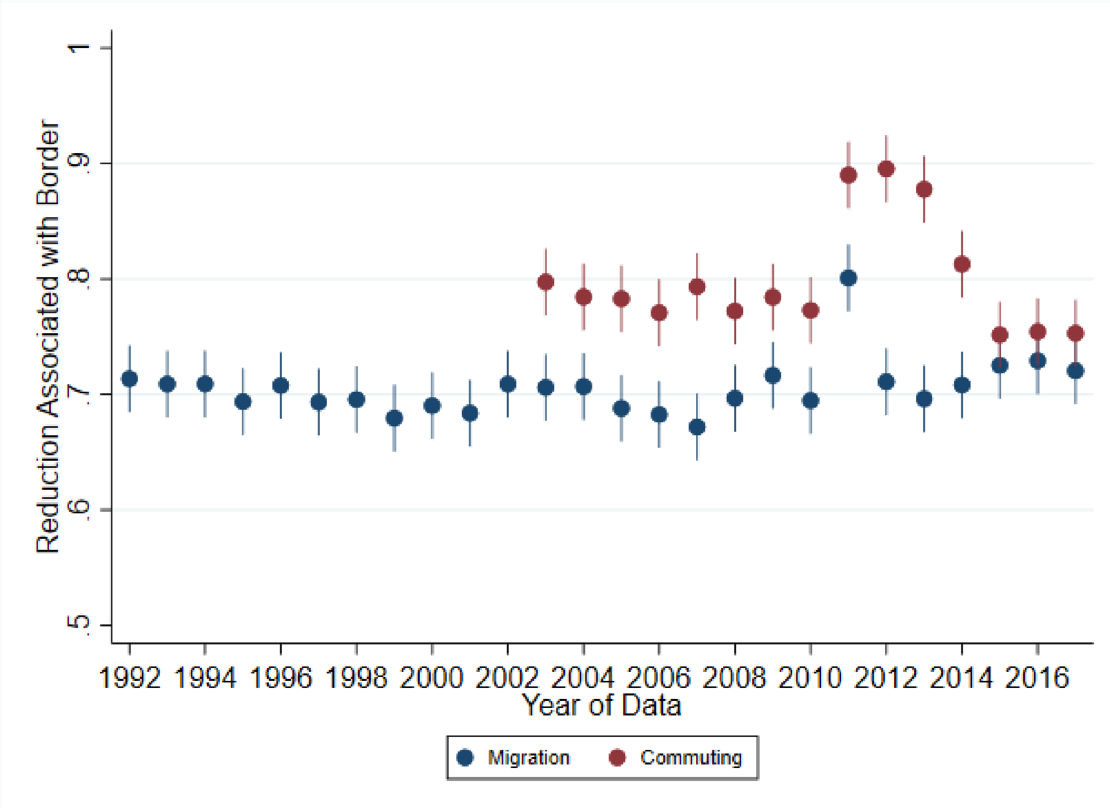
Figure A1: County-to-County Migration and Commute Rates by Distance for Same-State and Different-State County Pairs, Regression Estimates



NOTE: Outcome in the left panel is number of migrants per 1,000 people at the origin county using the IRS SOI county-to-county flows from 2017. Outcome in the right panel is the number of commuters per 1,000 people at the origin county using the LODES origin-destination employment statistics aggregated to the county level from 2017. Point estimates from Equation (1) are plotted with 95 percent confidence intervals.

SOURCE: Author's own calculations using the 2017 IRS SOI and 2017 LODES.

Figure A2: Relationship over Time: Impact of State Borders on County-to-County Migration and Commuting from 1992 to 2017



NOTE: The reduction in migration (blue) and commuting (red) associated with state borders for each year from 1992 to 2017 are plotted with 95 percent confidence intervals. Average migration rates for same-state and cross-state county pairs in the 20-mile bin are plotted for 1992–2017. These estimates are obtained by regressing Equation (2) for each year from 1992 to 2017 separately, then estimating the ratio of area under the curve for same-state and cross-state county pairs between 15 and 60 miles apart. In 2011, the IRS extended the data collection period from September to the end of the year, which includes more complicated returns. They also used the information of other household members to identify links over time. Prior to 2013, county-to-county flows below 10 tax units (households) was suppressed. In 2013 that limit was increased to 20.

SOURCE: Author's own calculations using the IRS county-to-county flows from 1992 to 2017, LODES data from 2003 to 2017.

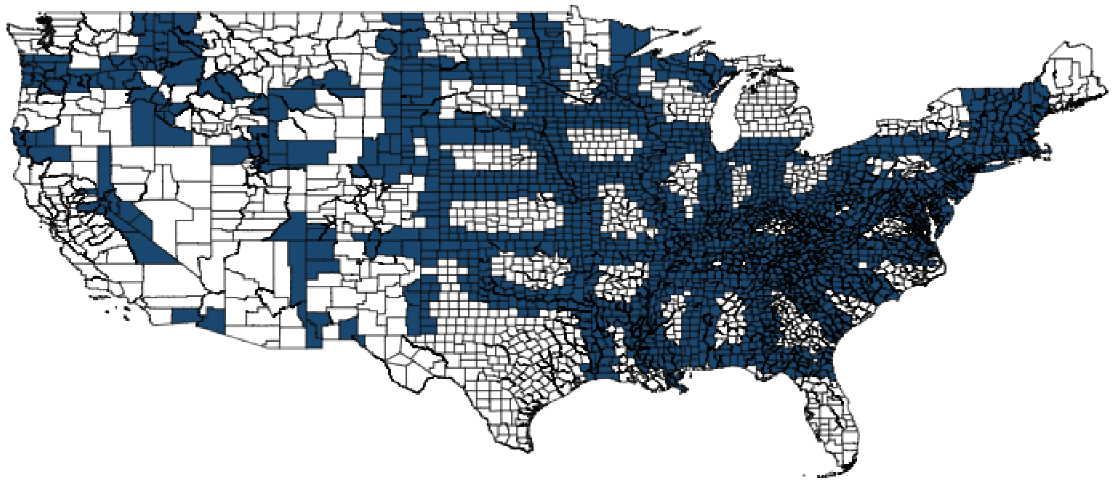
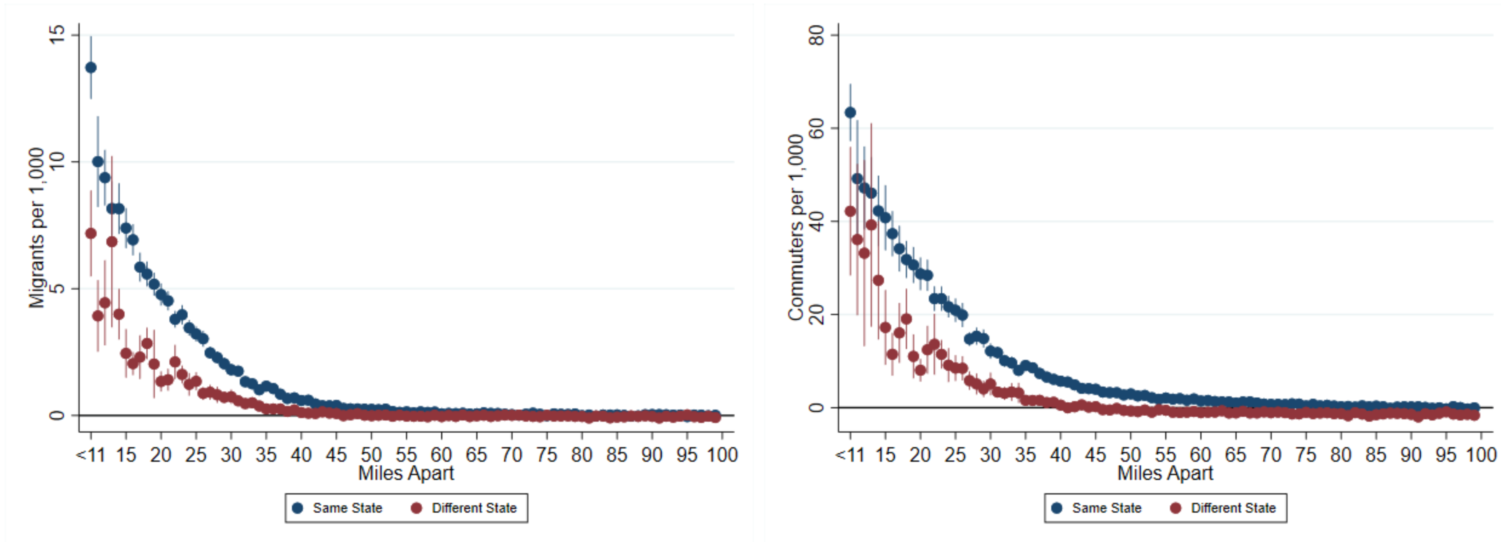


Figure A3: Counties within 60 Miles of a County in a Different State

NOTE: Counties with a population centroid less than 60 miles from the population centroid of another county in a different state are indicated.

SOURCE: Author's own calculations.

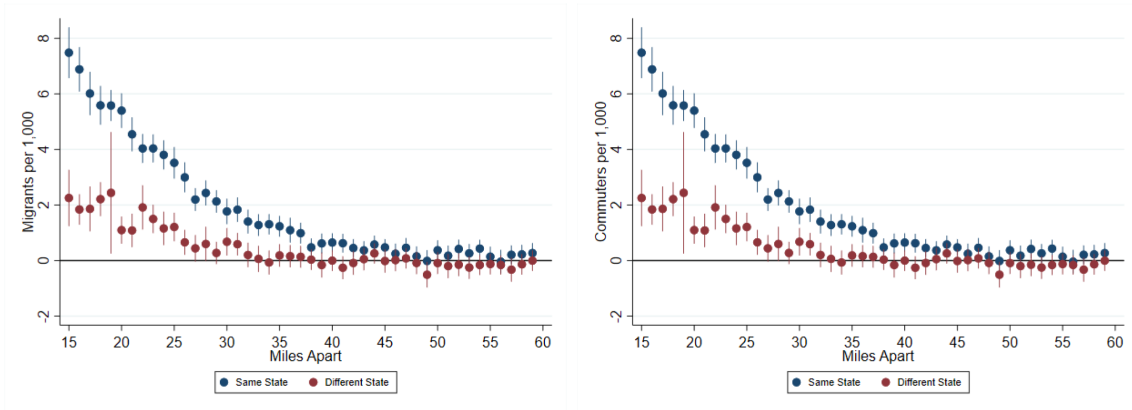
Figure A4: County-to-County Migration and Commute Rates by Distance and for Same-State and Different-State Counties, Including Closer and Farther Distance Bins



NOTE: Outcome in the left panel is number of migrants per 1,000 people at the origin county using the IRS SOI county-to-county flows from 2017. Outcome in the right panel is the number of commuters per 1,000 people at the origin county using the LODES origin-destination employment statistics aggregated to the county level from 2017. Point estimates are obtained by estimating an equation similar to Equation (2), but more distance bins are added. The "<11 bin" includes all pairs less than 11 miles apart. Ninety-five-percent confidence intervals are provided.

SOURCE: Author's own calculations using the 2017 IRS SOI and 2017 LODES.

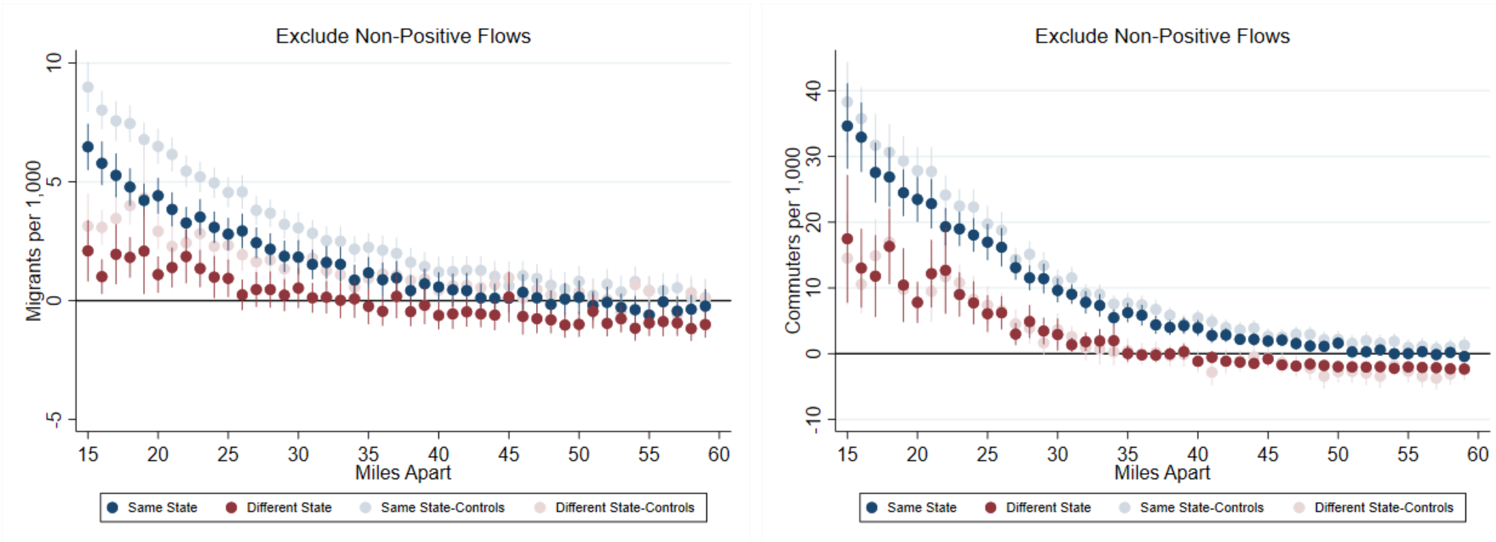
Figure A5: Impact of State Borders on Migration and Commuting in Cross-Border Designated Market Areas



NOTE: Coefficients from Equation (2) are plotted. Migration is plotted in the left panel, commuting in the right. The sample is restricted to include only counties in DMAs that cross state borders and to include only county pairs that are in the same DMA. Estimation controls for origin fixed effects, destination fixed effects, and differences between the origin and destination county in labor market measures (the unemployment rate, employment-to-population ratio, average weekly wages, number of establishments), differences in industry shares (share in natural resources and mining, construction, manufacturing, trade, information, finance, professional, education and health, hospitality, public sector, and all others), differences in demographics (total population, share female, non-Hispanic White, non-Hispanic Black, non-Hispanic other, Hispanic, under 20, 20–34, 35–49, 50–64, and 65 and older), differences in natural amenities (the January average temperature, January average sunlight, July average temperature, July average humidity, and the USDA natural amenities scale), the 2016 presidential Republican vote share, differences in the county housing price index converted to dollars using the median house value from 2000, and differences in average third- through eighth-grade math and reading language arts test scores. Ninety-five-percent confidence intervals are provided.

SOURCE: Author's own calculations using the 2017 IRS SOI and 2017 LODES.

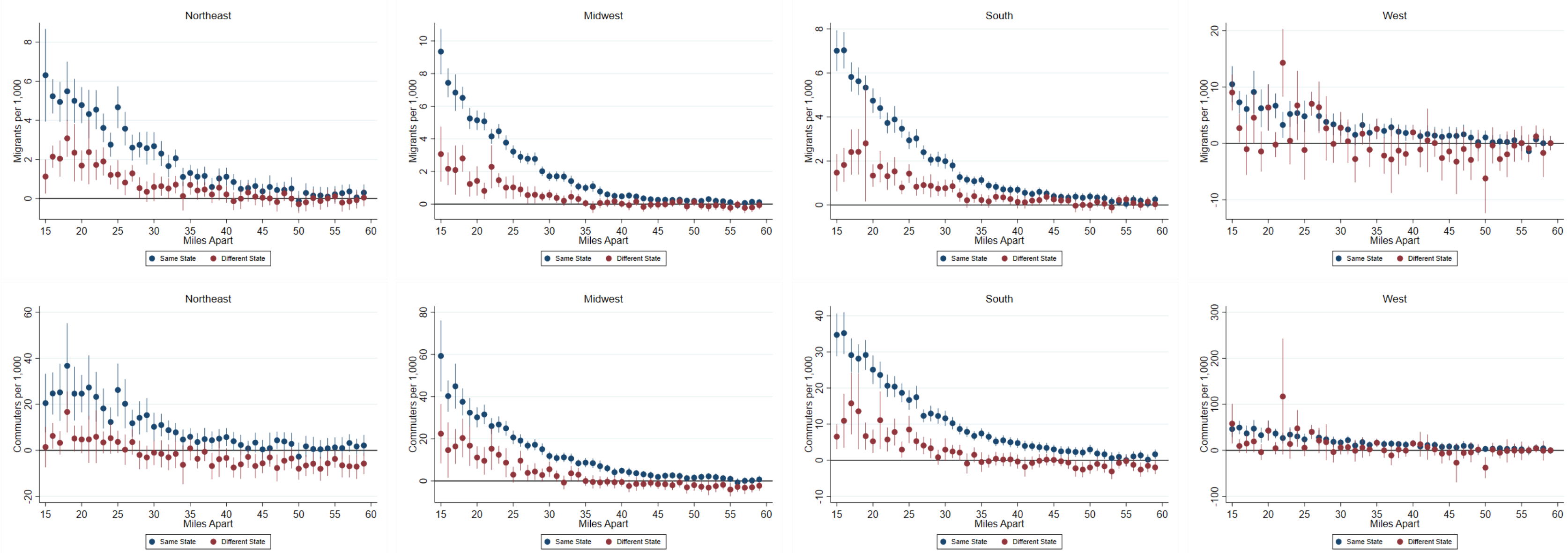
Figure A6: Impact of State Borders on Migration and Commute, Excluding County-to-County Flows of Zero



NOTE: Outcome in the left panel is number of migrants per 1,000 people at the origin county using the IRS SOI county-to-county flows from 2017. Outcome in the right panel is the number of commuters per 1,000 people at the origin county using the LODES origin-destination employment statistics aggregated to the county level from 2017. Point estimates from Equations (1) and (2) are plotted with 95 percent confidence intervals. Sample restricted to exclude county-to-county observations where the migration/commute rate is zero. Some of these zero flows are artificially suppressed for data privacy.

SOURCE: Author's own calculations using the 2017 IRS SOI and 2017 LODES.

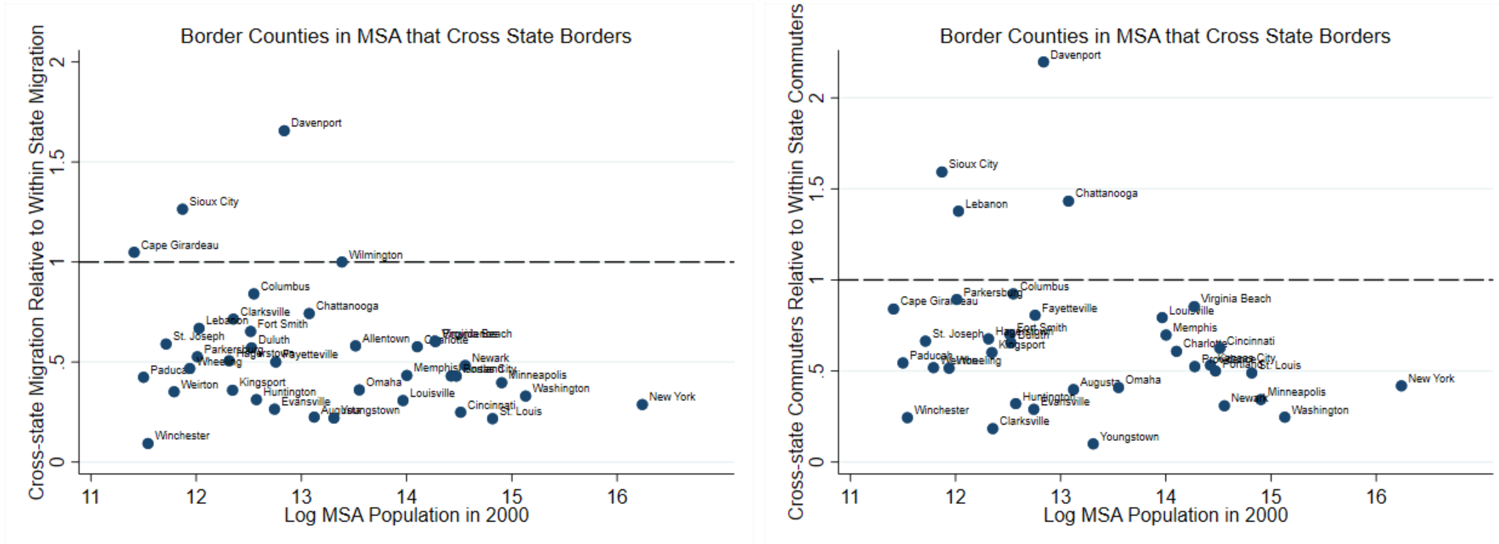
Figure A7: Impact of State Borders on Migration and Commuting, by Census Region



NOTE: Coefficients are plotted from Equation (2), estimated separately by origin-county census region. Migration is plotted in the top panel, commuting in the bottom. Estimation controls for origin fixed effects, destination fixed effects, and differences between the origin and destination county in labor market measures (the unemployment rate, employment-to-population ratio, average weekly wages, number of establishments), differences in industry shares (share in natural resources and mining, construction, manufacturing, trade, information, finance, professional, education and health, hospitality, public sector, and all others), differences in demographics (total population, share female, non-Hispanic White, non-Hispanic Black, non-Hispanic other, Hispanic, under 20, 20–34, 35–49, 50–64, and 65 and older) differences in natural amenities (the January average temperature, January average sunlight, July average temperature, July average humidity, and the USDA natural amenities scale), the 2016 presidential Republican vote share, differences in the county housing price index, converted to dollars using the median house value from 2000, and differences in average third- through eighth-grade math and reading language arts test scores. Ninety-five-percent confidence intervals are provided.

SOURCE: Author's own calculations using the 2017 IRS SOI and 2017 LODES.

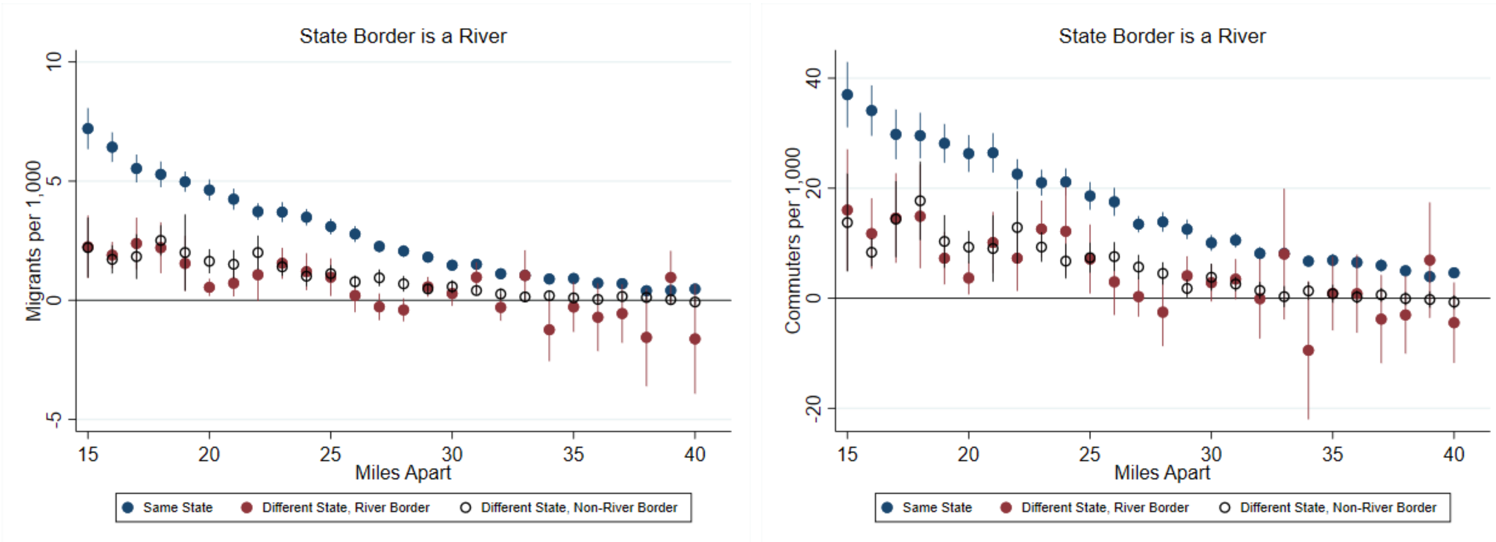
Figure A8: Impact of State Borders on Migration and Commute, Estimated by MSA



NOTE: The ratio of cross-border migration/commuting relative to within-state migration/commuting for county pairs in the same MSA is plotted for each MSA that crosses state borders and has more than one county in each state.

SOURCE: Author's own calculations using the 2017 IRS SOI and 2017 LODES.

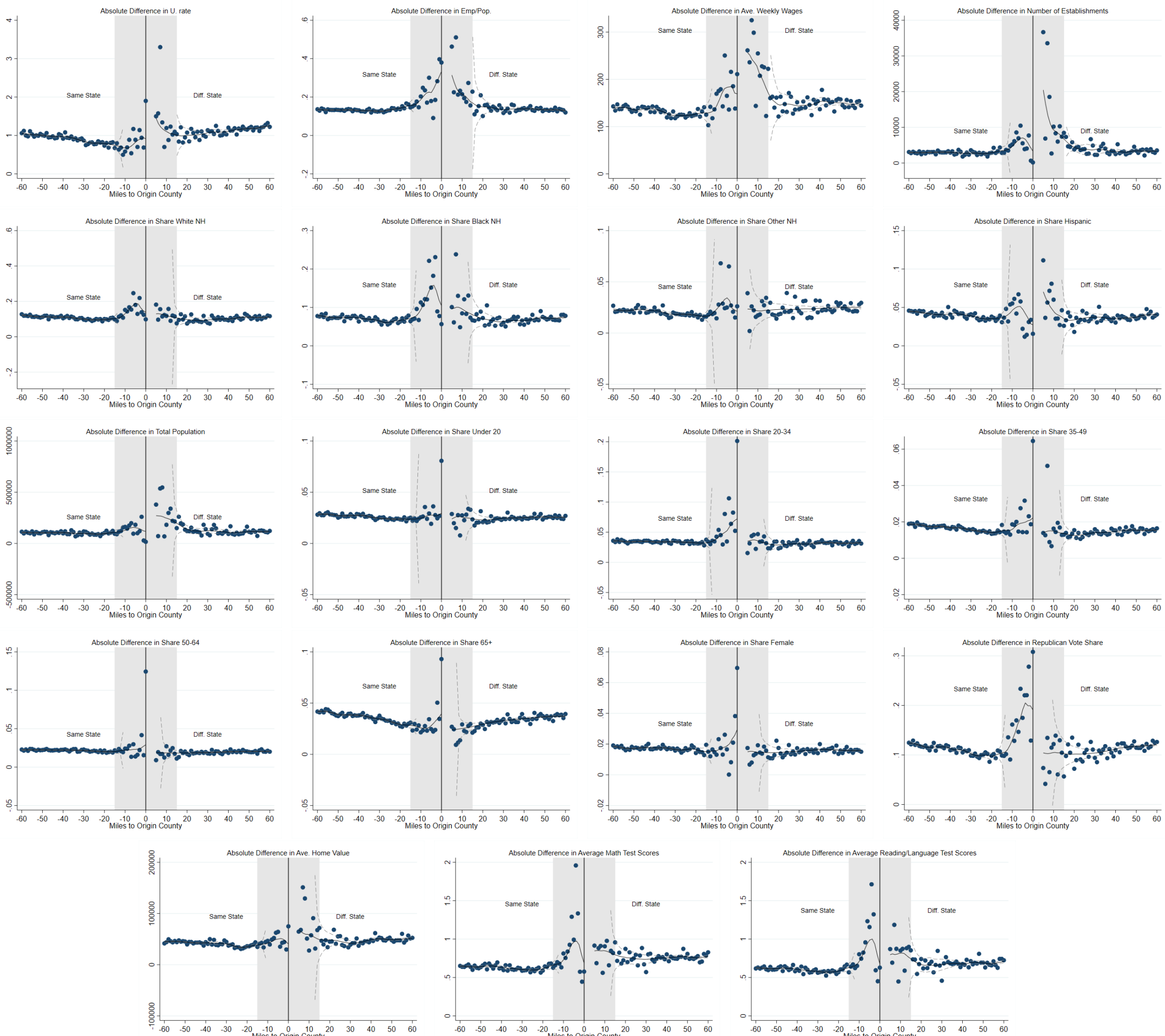
Figure A9: Impact of State Borders, States Separated by Rivers vs. Arbitrary Borders



NOTE: Sample restricted to counties that are less than 60 miles from another county in a different state. Coefficients from Equation (6), where the characteristic is the presence of a river border between states. Ninety-five-percent confidence intervals are provided.

SOURCE: Author's own calculations using the 2017 IRS SOI and 2017 LODES.

Figure A10: Role of Differences in Utility: Changes in Local Characteristics at State Border



NOTE: Average difference in characteristics in one-mile bins for county pairs in the same state and different states are plotted with local linear polynomial regressions and 95-percent confidence intervals. There are few county pairs within 15 miles of each other, and these are excluded from my main analysis. These pairs are shaded in gray for reference.

SOURCE: Author's own calculations using the QCEW 2017, SEER 2017 data, NCSL 2016 vote data, FHFA HPI 2017 data, and SEDA 2008–2017 test score data.

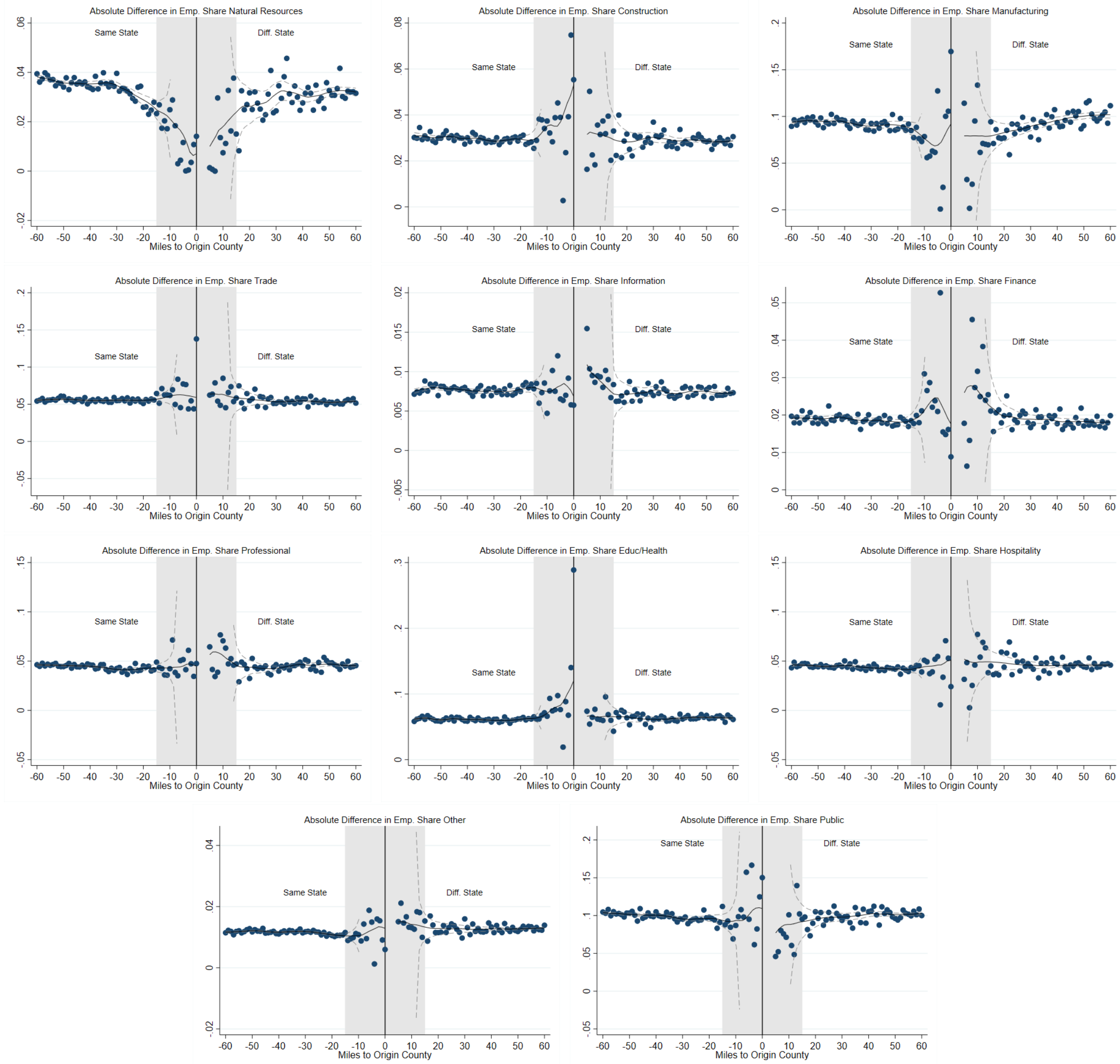
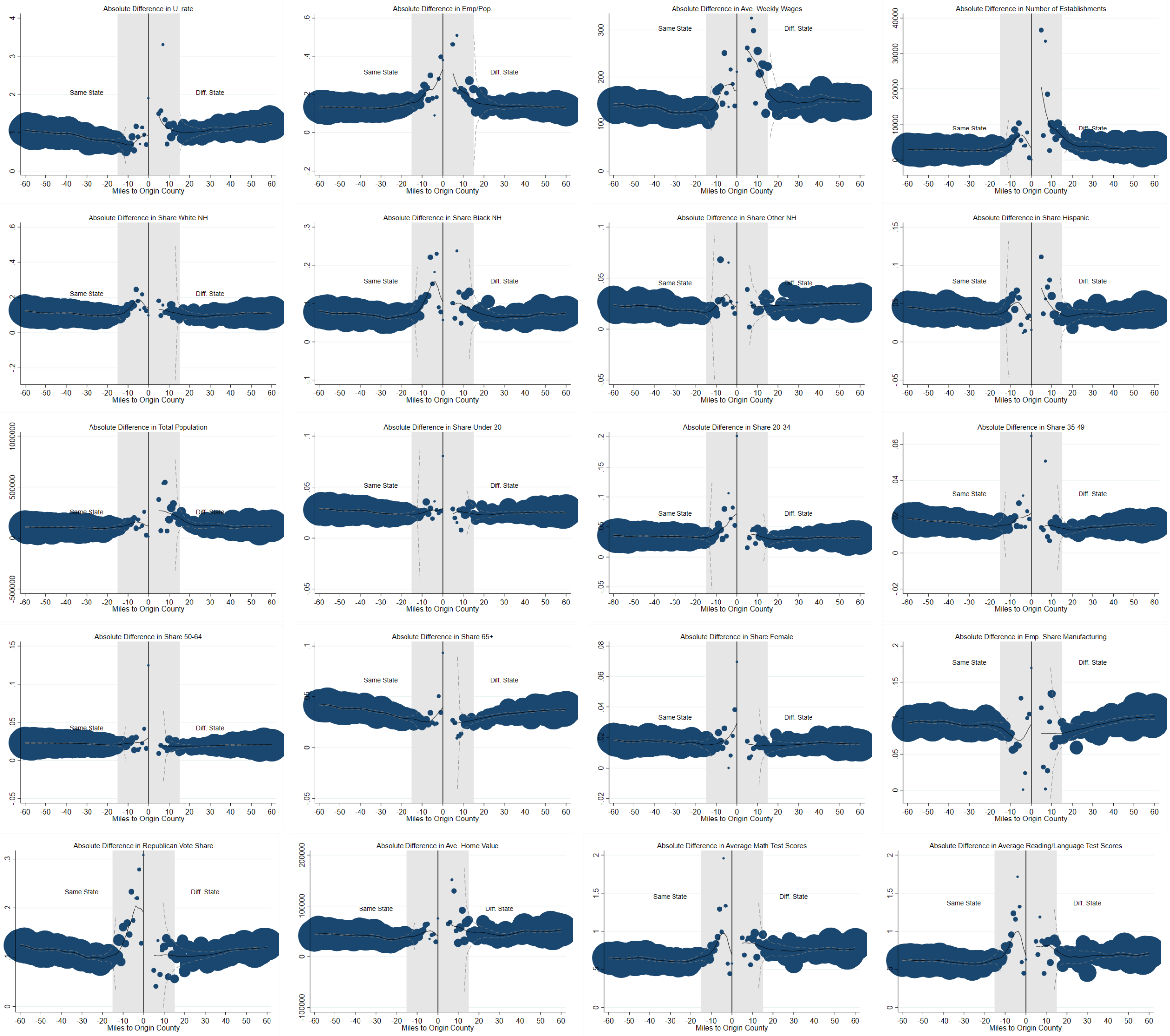


Figure A11: Role of Differences in Utility: Changes in Local Industry Composition at State Border

NOTE: Average difference in characteristics in one-mile bins for county pairs in the same state and different states are plotted with local linear polynomial regressions and 95 percent confidence intervals. There are few county pairs within 15 miles of each other, and these are excluded from my main analysis. These pairs are shaded in gray for reference.

SOURCE: Author's own calculations using the QCEW 2017 data.

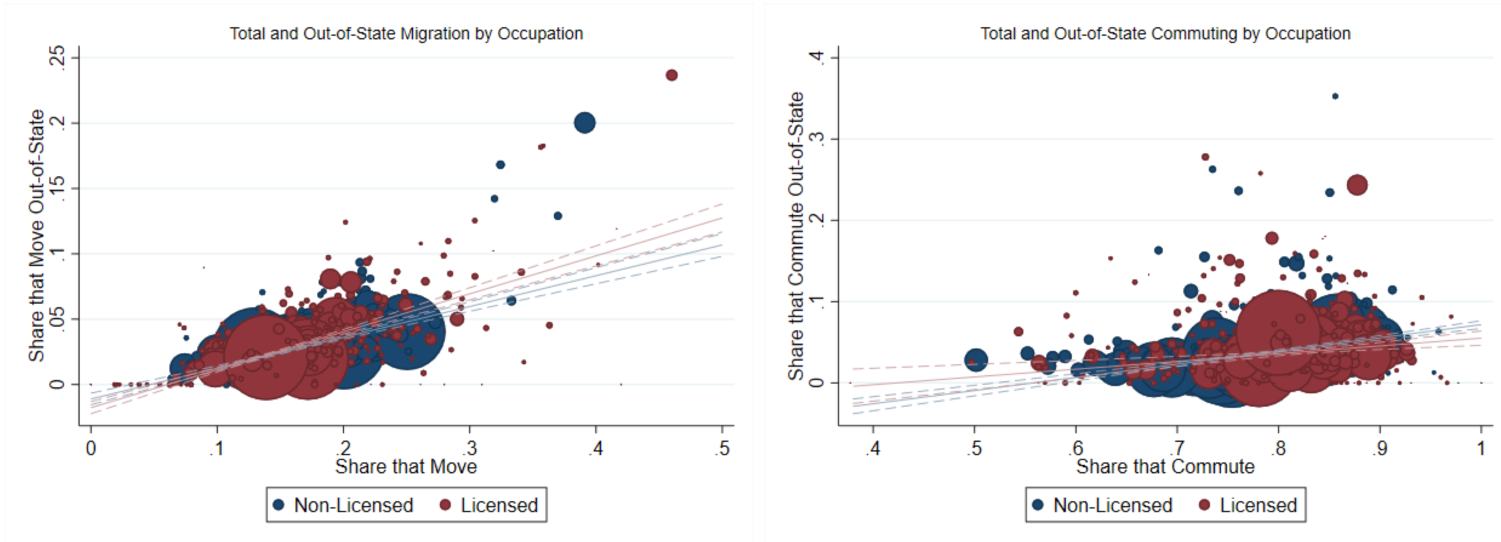
Figure A12: Role of Differences in Utility: Changes in Local Characteristics at State Border, Weighted Points



NOTE: Average difference in characteristics in one-mile bins for county pairs in the same state and different states are plotted with local linear polynomial regressions and 95 percent confidence intervals. Points are weighted by the number of county pairs. There are few county pairs within 15 miles of each other, and these are excluded from my main analysis. These pairs are shaded in gray for reference.

SOURCE: Author's own calculations using the QCEW 2017, SEER 2017 data, NCSL 2016 vote data, FHFA HPI 2017 data, and SEDA 2008–2017 test score data.

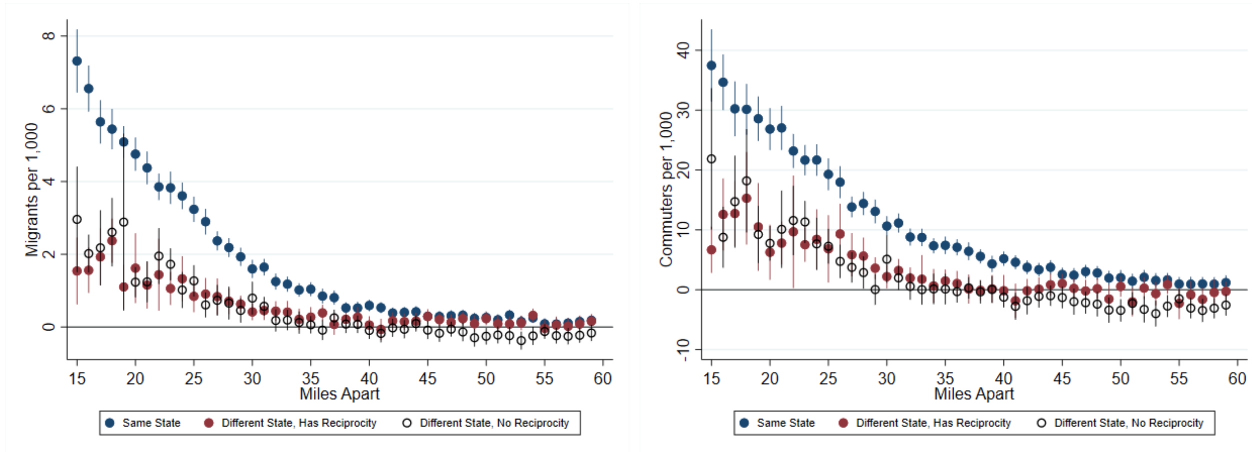
Figure A13: Occupation-Level Cross-State Migration and Commuting by Occupational Licensing



NOTE: Each point represents the migration/commuting rates by occupational code and governmental licensure status using the 2015–2017 ACS. For each occupation there are two points, one for workers in licensed states and time periods, one for workers in nonlicensed states and time periods. Sample restricted to occupations that are licensed in some states but not all. The size of the point is scaled to represent the population-weighted number of people in the occupation. The blue linear prediction is for nonlicensed occupations. The pink linear prediction is for licensed occupations. Linear predictions include 95-percent confidence intervals.

SOURCE: Author's own calculations using the 2015–2017 ACS.

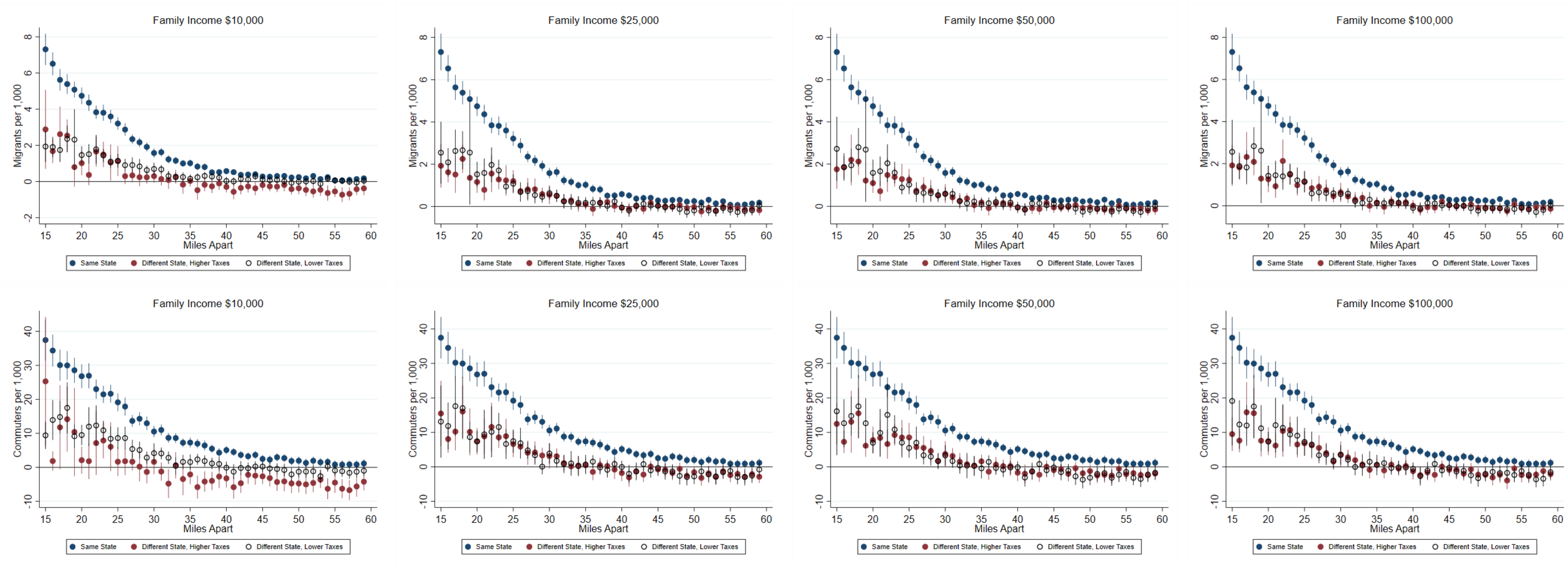
Figure A14: Role of State Income Taxation Reciprocity Agreements



NOTE: Coefficients from Equation (6) are plotted, where the high/low difference is whether the origin and destination state have a tax reciprocity agreement. Migration is plotted in the left panel, commuting in the right. The same controls are included as listed in the notes for Figure 1. Ninety-five-percent confidence intervals are provided.

SOURCE: Author's own calculations using the 2017 IRS SOI and 2017 LODES.

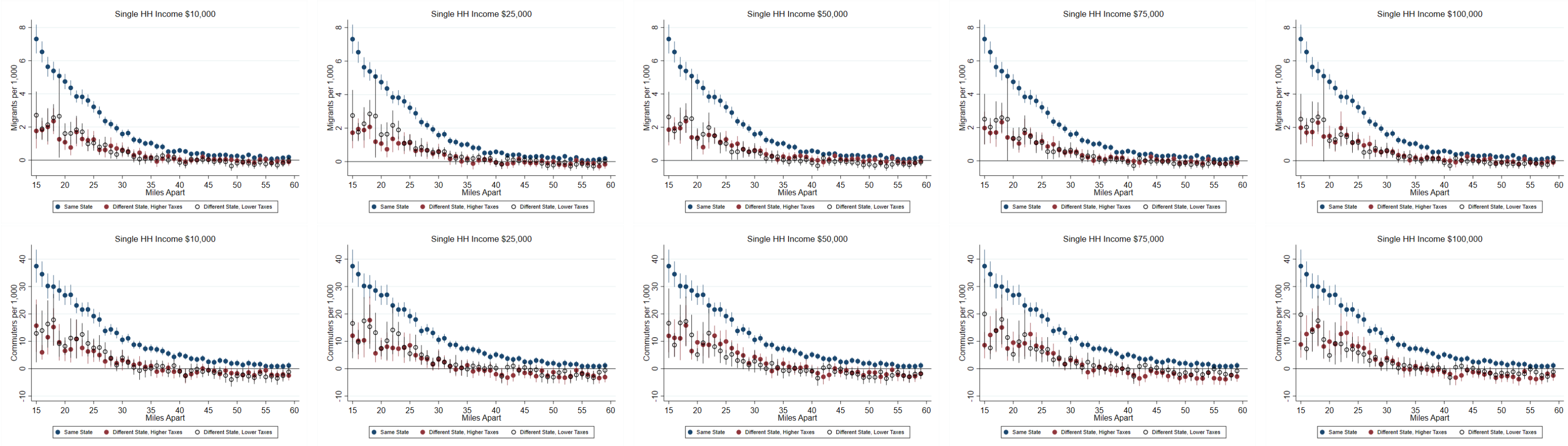
Figure A15: Role of State Income Taxation: Migration and Commuting across State Borders, Married, Filing Jointly with Two Dependents



NOTE: Coefficients from Equation (6) are plotted. Migration is plotted in the top panel, commuting in the bottom. The point estimates represent differences by state+federal income tax burdens for a married household with two dependents with various levels of annual income. The same controls are included as listed in the notes for Figure 1. Ninety-five percent confidence intervals are provided.

SOURCE: Author's own calculations using the 2017 IRS SOI and 2017 LODES.

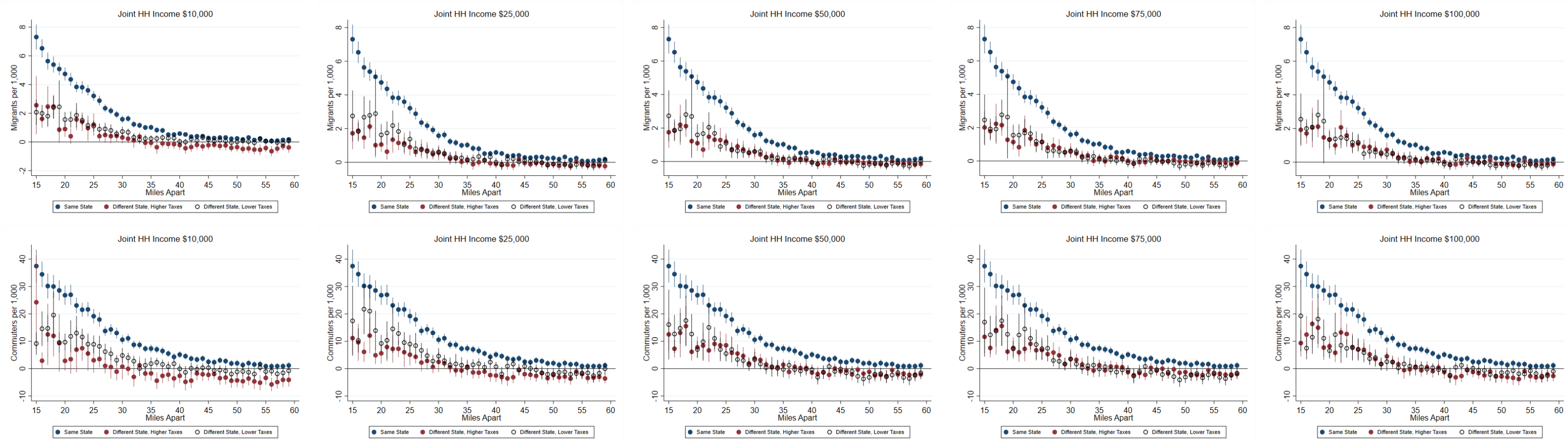
Figure A16: Role of State Income Taxation: Migration and Commuting across State Borders, for a Single Individual



NOTE: Coefficients from Equation (6) are plotted. Migration is plotted in the top panel, commuting in the bottom. The point estimates represent differences by state+federal income tax burdens for a single individual with various levels of annual income. The same controls are included as listed in the notes for Figure 1. Ninety-five percent confidence intervals are provided.

SOURCE: Author's own calculations using the 2017 IRS SOI and 2017 LODES.

Figure A17: Role of State Income Taxation: Migration and Commuting across State Borders, for a Joint Filer with no Dependents



NOTE: Coefficients from Equation (6) are plotted. Migration is plotted in the top panel, commuting in the bottom. The point estimates represent differences by state+federal income tax burdens for a married, joint household with no children with various levels of annual income. The same controls are included as listed in the notes for Figure 1. Ninety-five percent confidence intervals are provided.

SOURCE: Author's own calculations using the 2017 IRS SOI and 2017 LODES.

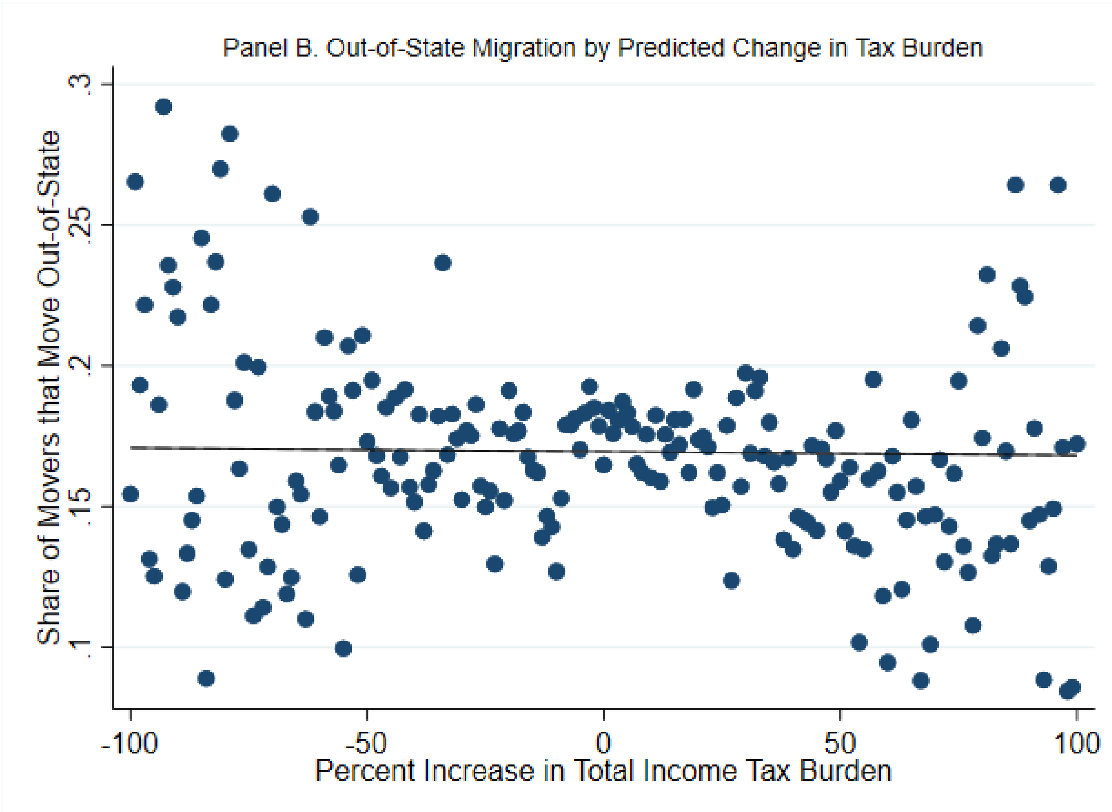
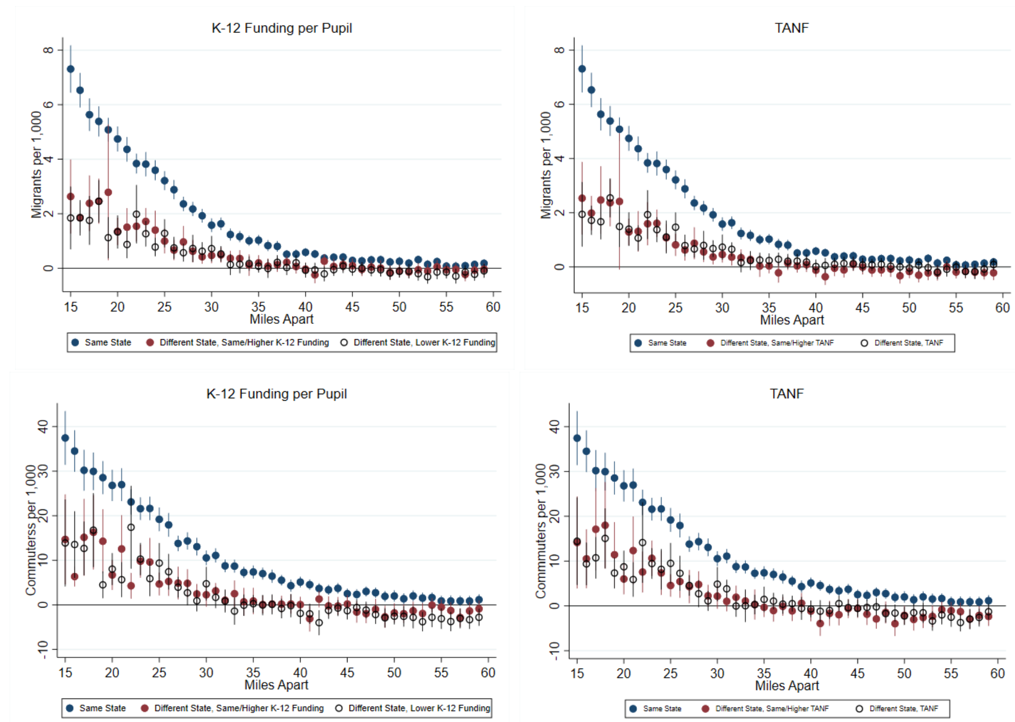


Figure A18: Share of Households That Move Out-of-State by Expected Percent Increase in Tax Burden

NOTE: Sample is limited to families originally living in a commuting zone that crosses a state border. Each point represents the share of migrants that moved across state borders, by the difference in the average total income tax burden associated with moving between the origin state and the other state(s) in the commuting zone. If there are more than two states in a commuting zone, the average total income tax burden is used. Results are similar if instead the maximum or minimum total income tax burden is used. The black line indicates the linear relationship.

SOURCE: Author's own calculations using the 2012–2017 ACS Microdata.

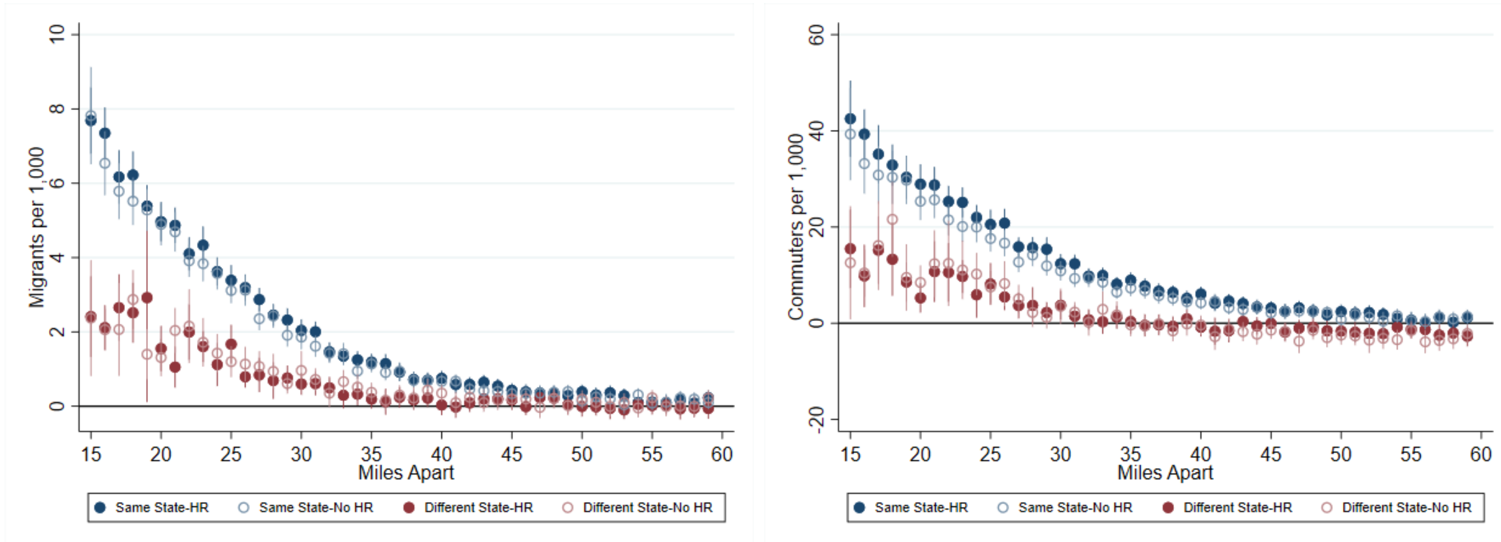
Figure A19: Impact of State Borders on Migration and Commuting by Pre-K–12 Per Pupil Spending and TANF Generosity



NOTE: Coefficients from Equation (6) are plotted. Migration is plotted in the top panel, commuting in the bottom. The left panel plots differences by pre-K–12 per-pupil public school spending. The right panel plots differences by the TANF benefit rate. Controls include origin fixed effects, destination fixed effects, and differences between the origin and destination county in labor market measures (the unemployment rate, employment-to-population ratio, average weekly wages, number of establishments), differences in industry shares (share in natural resources and mining, construction, manufacturing, trade, information, finance, professional, education and health, hospitality, public sector, and all others), differences in demographics (total population, share female, non-Hispanic White, non-Hispanic Black, non-Hispanic other, Hispanic, under 20, 20–34, 35–49, 50–64, and 65 and older) differences in natural amenities (the January average temperature, January average sunlight, July average temperature, July average humidity, and the USDA natural amenities scale), the 2016 presidential Republican vote share, differences in the county housing price index, converted to dollars using the median house value from 2000, and differences in average third- through eighth-grade math and reading language arts test scores. Ninety-five percent confidence intervals are provided.

SOURCE: Author's own calculations using the IRS county-to-county flows from 2017.

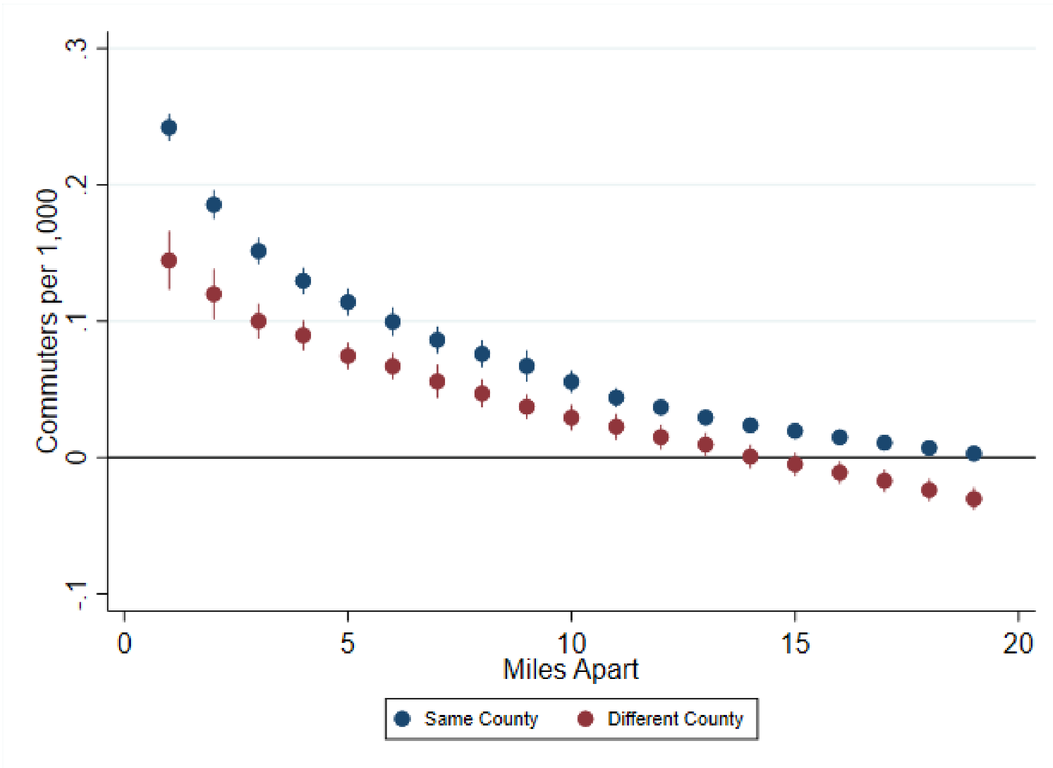
Figure A20: Impact of State Borders on Migration and Commuting by County Home Rule Regulation



NOTE: Coefficients from Equation (6) are plotted. Migration is plotted on the left, commuting on the right. Differences by the presence of Home Rule laws (as reported by Shoag et al., 2019). Controls include origin fixed effects, destination fixed effects, and differences between the origin and destination county in labor market measures (the unemployment rate, employment-to-population ratio, average weekly wages, number of establishments), differences in industry shares (share in natural resources and mining, construction, manufacturing, trade, information, finance, professional, education and health, hospitality, public sector, and all others), differences in demographics (total population, share female, non-Hispanic White, non-Hispanic Black, non-Hispanic other, Hispanic, under 20, 20–34, 35–49, 50–64, and 65 and older) differences in natural amenities (the January average temperature, January average sunlight, July average temperature, July average humidity, and the USDA natural amenities scale), the 2016 presidential Republican vote share, differences in the county housing price index, converted to dollars using the median house value from 2000, and differences in average third- through eighth-grade math and reading language arts test scores. Ninety-five percent confidence intervals are provided.

SOURCE: Author's own calculations, using the IRS county-to-county flows from 2017.

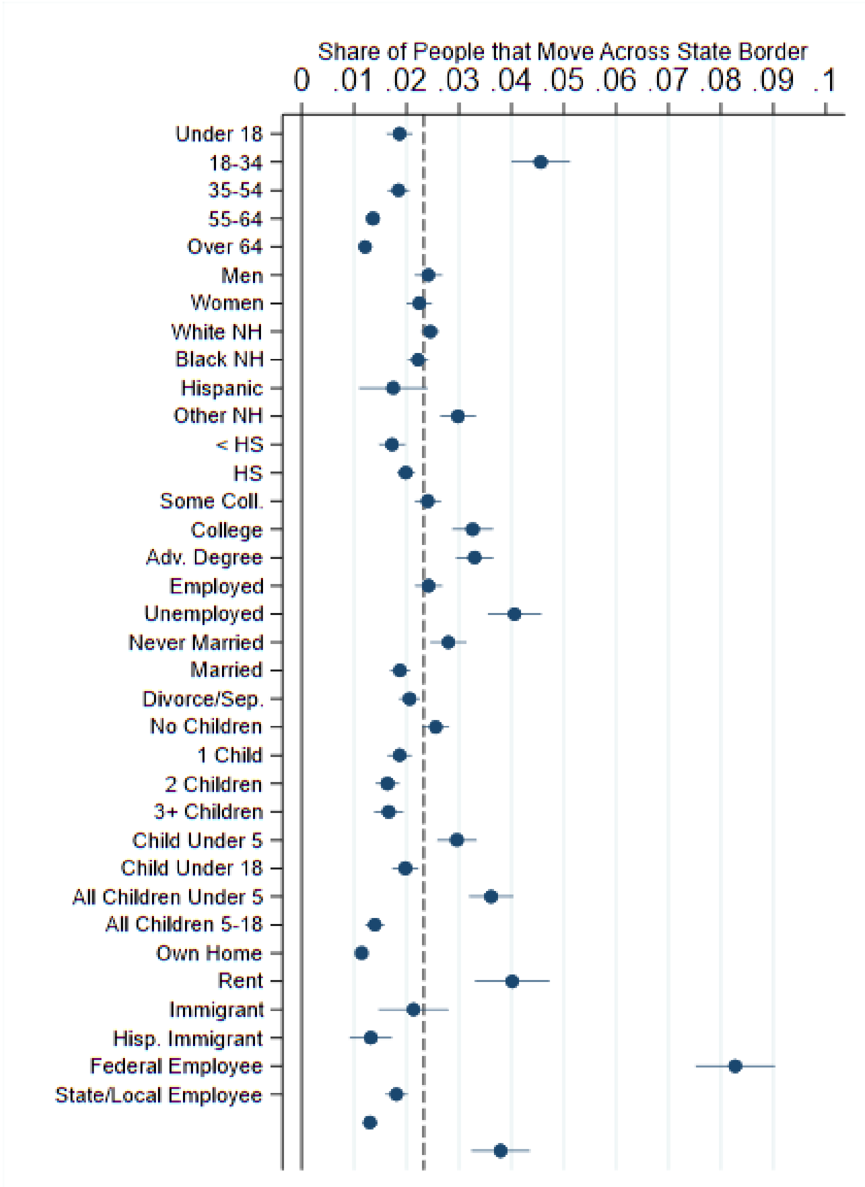
Figure A21: Census Tract-to-Tract Commute Rates by Distance for Same-County and Different-County Tract Pairs



NOTE: The outcome is the number of commuters per 1,000 people at the origin tract using the LODES origin-destination employment statistics aggregated to the tract level from 2017. "Miles Apart" is the distance between the population-weighted tract centroids. Ninety-five percent confidence intervals are provided.

SOURCE: Author's own calculations using the 2017 LODES.

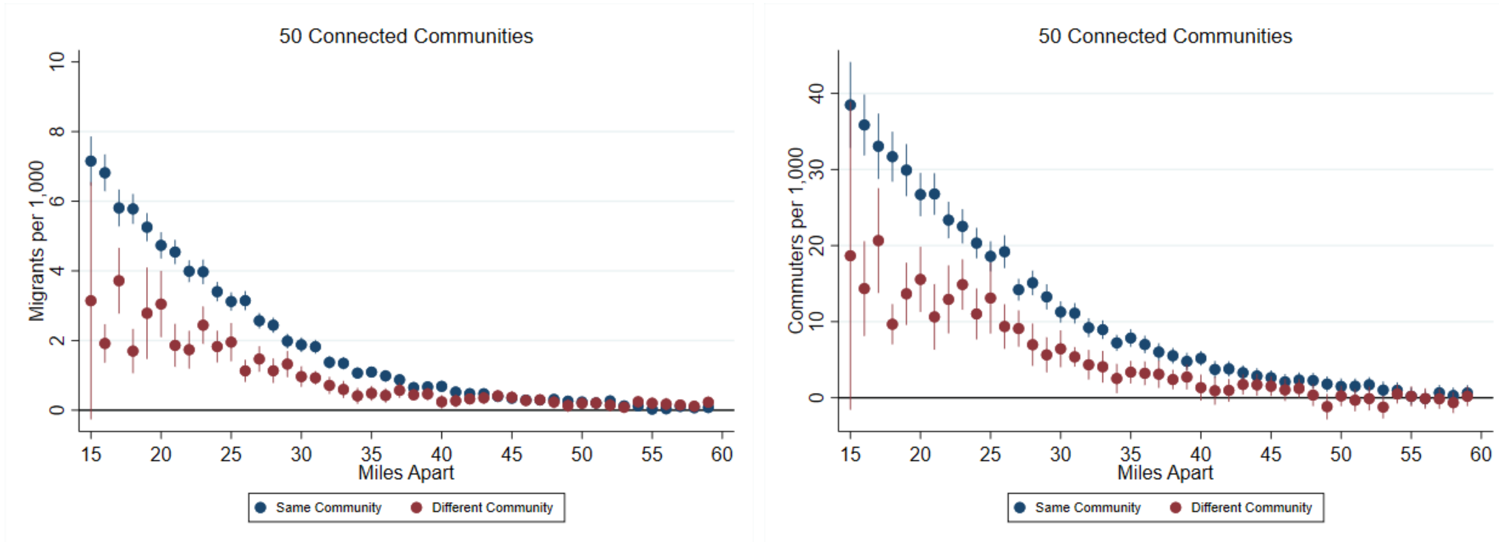
Figure A22: Role of Demographics: Cross-State Migration across Demographic Groups in the ACS, All Individuals



NOTE: Each point represents the share of individuals that moved across state borders within the past year, according to the 2012–2017 ACS.

SOURCE: Author's own calculations using the 2012–2017 ACS.

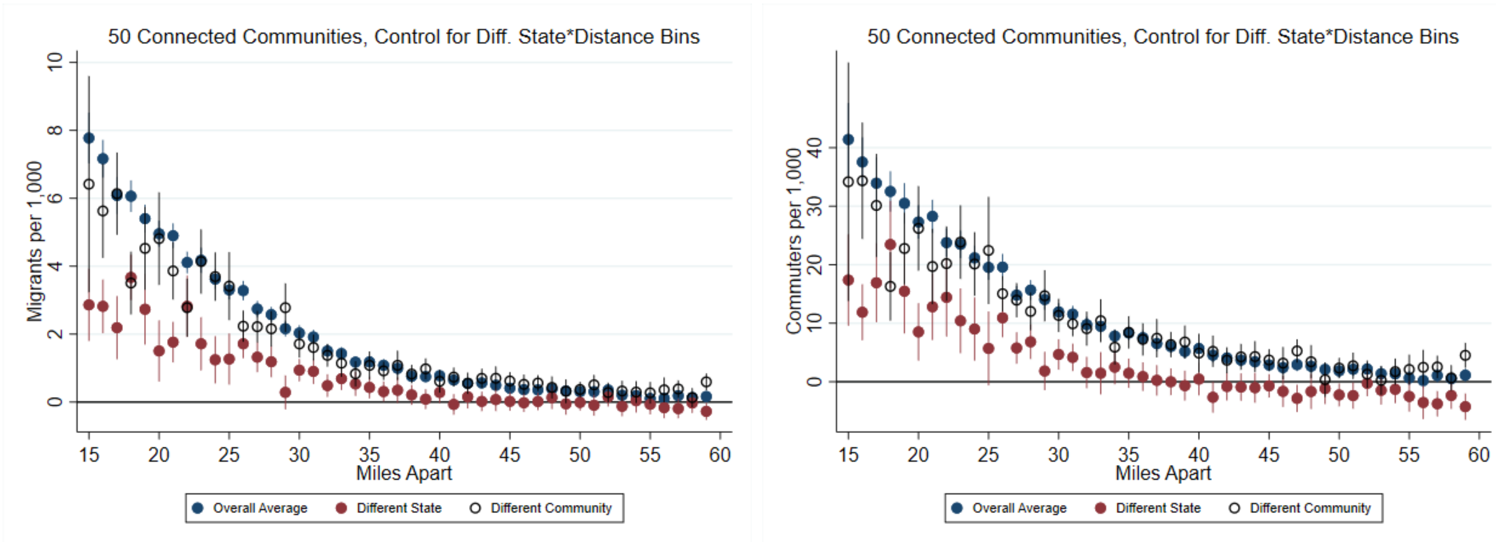
Figure A23: Impact of Pseudo Connected Community Borders on Migration and Commuting



NOTE: Sample restricted to counties that are less than 60 miles from another county in a different state. The outcomes are migration rates (left) and commuting rates (right). Each panel plots the coefficients from Equation (2) but includes the full set of connected-community-border-by-distance interactions rather than state-border-by-distance interactions. Ninety-five percent confidence intervals are provided.

SOURCE: Author's own calculations using the 2016 SCI, 2017 IRS SOI, and 2017 LODES.

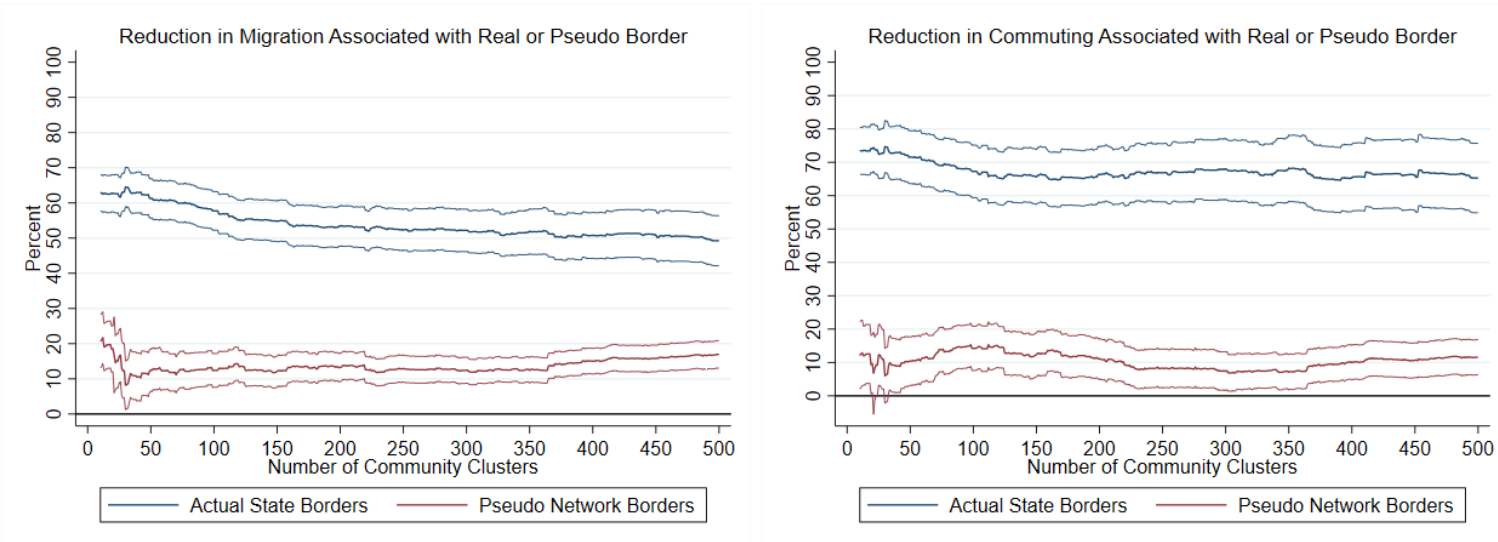
Figure A24: Horserace Regression: Relative Importance of Physical State Borders versus Pseudo Connected Community Borders, Weighted by Connected Community Border Persistence



NOTE: Sample restricted to counties that are less than 60 miles from another county in a different state. The outcomes are migration rates (left) and commuting rates (right). Each panel plots the coefficients from Equation (2) but includes the full set of state-border-by-distance interactions and the connected-community-border-by-distance interactions. Observations are weighted with the following weights $(\mu - 0.5)^2$, in which μ is the fraction of times (out of 51) the counties are in a different connected community when all prespecified cluster numbers from 25 to 75 are included. The weights subtract 0.5 and are squared so that the more county pairs have the same assignment, the higher the weight. This captures greater confidence in the connected community assignment. Ninety-five percent confidence intervals are provided.

SOURCE: Author's own calculations using the 2016 SCI, 2017 IRS SOI, and 2017 LODES.

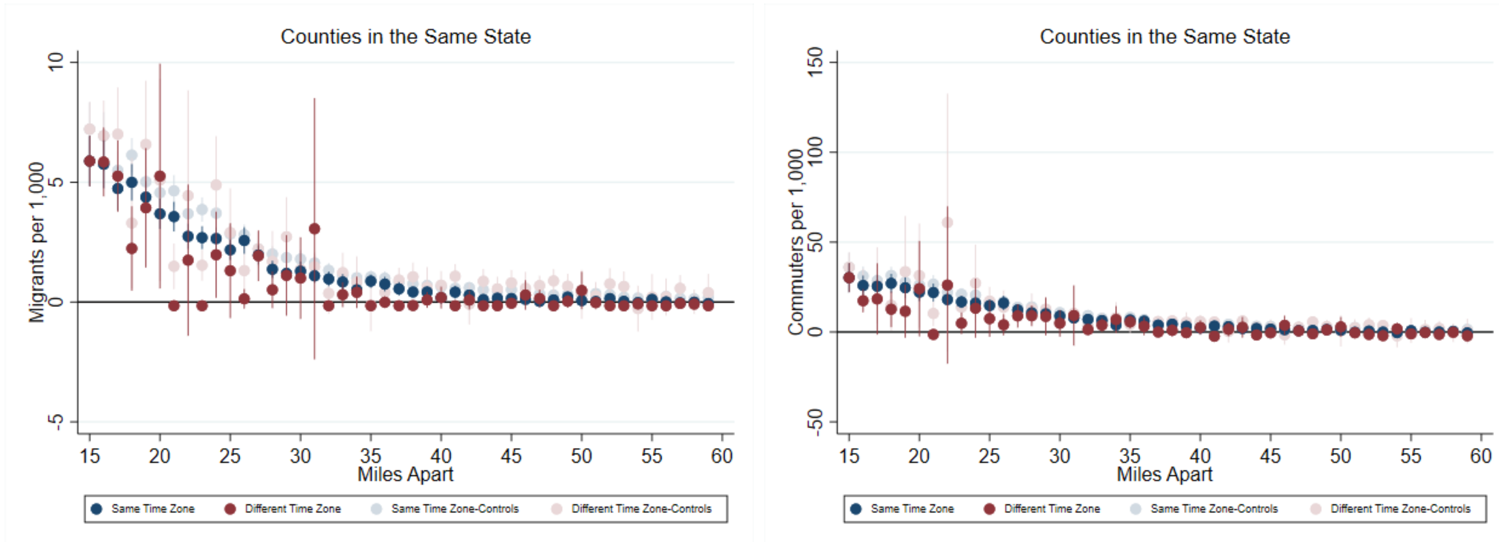
Figure A25: Horserace Regression: Relative Importance of Physical State Borders versus Pseudo Connected Community Borders for Various Prespecified Numbers of Connected Communities



NOTE: Sample restricted to counties that are less than 60 miles from another county in a different state. The outcomes are migration rates (left) and commuting rates (right). Each point is a measure of the gap in migration due to physical state borders or pseudo connected community borders from Equation (2) but includes the full set of state-border-by-distance interactions and the connected-community-border-by-distance interactions, where the prespecified number of connected communities is varied between 10 and 500. Ninety-five percent confidence intervals are provided.

SOURCE: Author's own calculations using the 2016 SCI, 2017 IRS SOI, and 2017 LODES.

Figure A26: County-to-County Migration and Commute Rates by Distance across Time Zone Borders among Counties in the Same State



NOTE: Outcome in the left panel is number of migrants per 1,000 people at the origin county using the IRS SOI county-to-county flows from 2017. Outcome in the right panel is the number of commuters per 1,000 people in the origin county using the LODES origin-destination employment statistics aggregated to the county level from 2017. Only counties in the same state, in states that span multiple time zones, are included. Distance is the distance between the population-weighted county centroids. The "Controls" specifications plots coefficients from Equation (2), accounting for origin fixed effects, destination fixed effects, and differences between the origin and destination county in labor market measures (the unemployment rate, employment-to-population ratio, average weekly wages, number of establishments), differences in industry shares (share in natural resources and mining, construction, manufacturing, trade, information, finance, professional, education and health, hospitality, public sector, and all others), differences in demographics (total population, share female, non-Hispanic White, non-Hispanic Black, non-Hispanic other, Hispanic, under 20, 20–34, 35–49, 50–64, and 65 and older) differences in natural amenities (the January average temperature, January average sunlight, July average temperature, July average humidity, and the USDA natural amenities scale), the 2016 presidential Republican vote share, differences in the county housing price index, converted to dollars using the median house value from 2000, and differences in average third- through eighth-grade math and reading language arts test scores. Ninety-five percent confidence intervals are provided.

SOURCE: Author's own calculations using the 2017 IRS SOI and 2017 LODES.

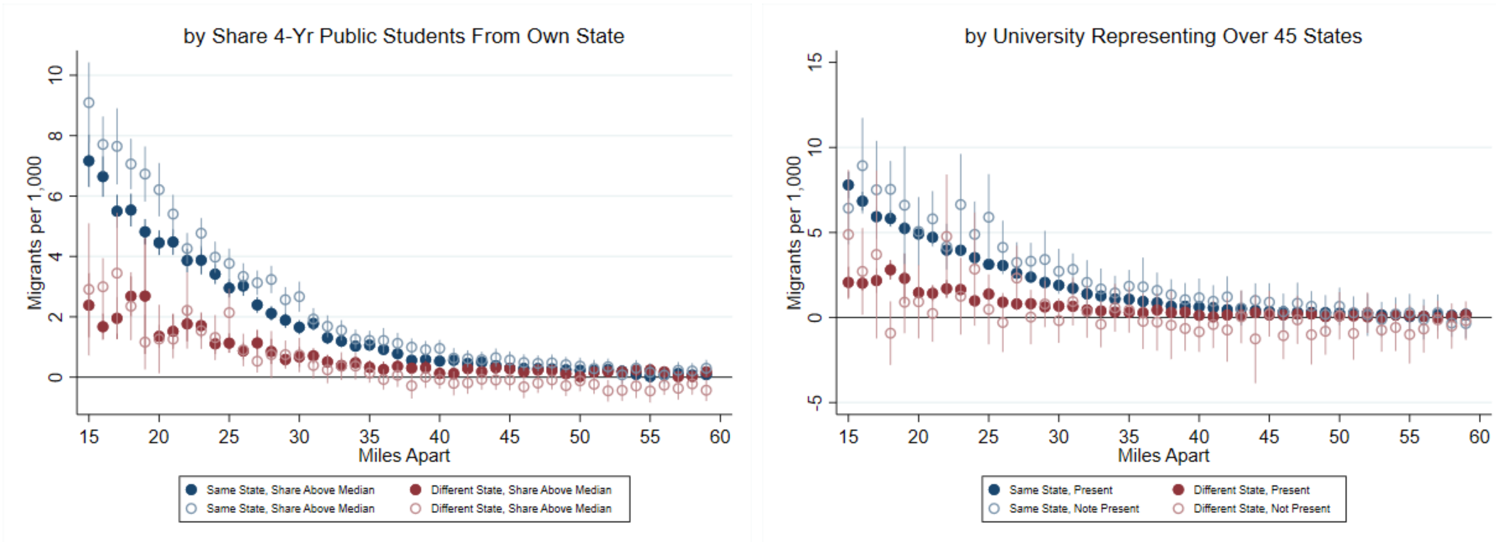


Figure A27: Identity from State Colleges: Migration by Interstate Connectivity of State Colleges

NOTE: Sample restricted to counties that are less than 60 miles from another county in a different state. Coefficients from Equation (2), in which the characteristic is whether public four-year institutions have an above- or below-median share of own state students (in the left Panel) and whether there is a university in the state with students from 45 or more states. Ninety-five percent confidence intervals are provided.

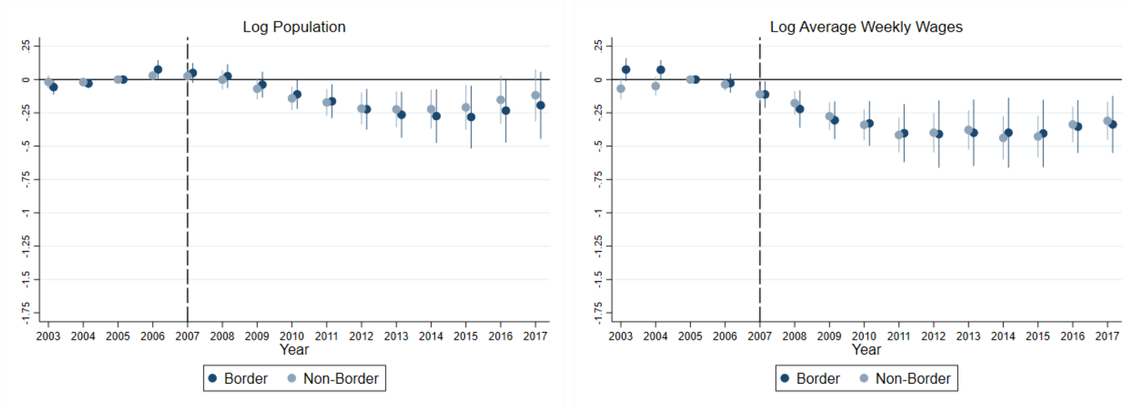
SOURCE: Author's own calculations using the 2017 IRS SOI.

Figure A28: Impact of State Borders on Labor Market Recovery after the Great Recession, Lagged Outcome Control

NOTE: These estimates are similar to those in Figure 11, but rather than including county fixed effects, I control for the county-level outcomes from 2005, as suggested by (Hershbein and Stuart, 2020). Event study coefficients are plotted with 95 percent confidence intervals and represent the percent change in outcomes, relative to 2005, for each percentage-point increase in commuting-zone employment reduction between 2007 and 2009. Observation at the county-by-year level. State-by-year fixed effects, as well as an indicator for being a border county interacted with year fixed effects, are included. Standard errors corrected for clustering at the commuting zone level.

SOURCE: Author's own calculations using the 2000–2017 QCEW and 2000–2017 IRS SOI.

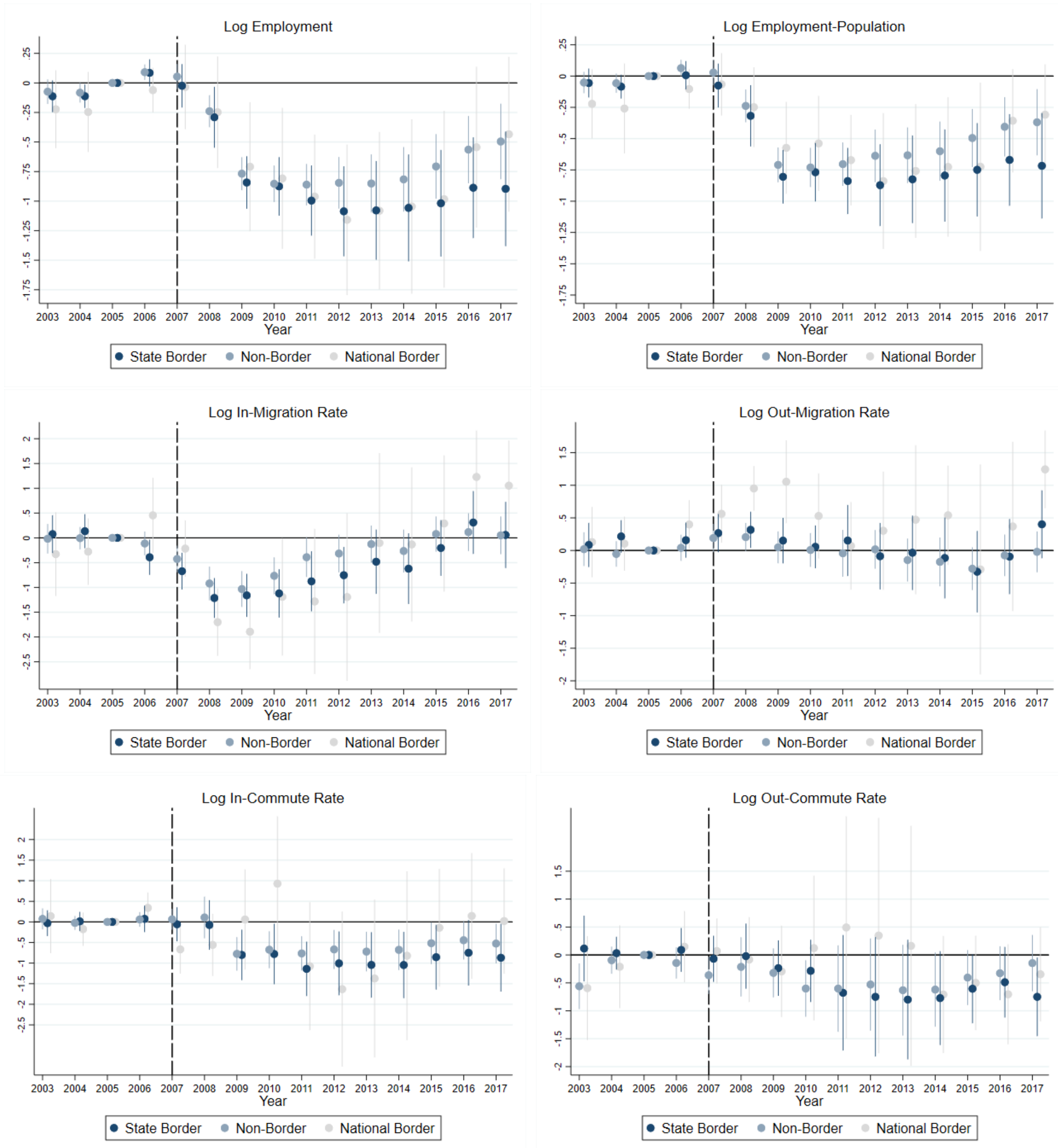
Figure A29: Impact of State Borders on Population and Wages after the Great Recession



NOTE: Event study coefficients from Equation (14) are plotted with 95 percent confidence intervals and represent the percent change in outcomes relative to 2005, for each percentage point increase in commuting-zone employment reduction between 2007 and 2009. Observation at the county by year level. County, state-by-year fixed effects, as well as an indicator for being a border county interacted with year fixed effects are included. Standard errors corrected for clustering at the commuting-zone level.

SOURCE: Author's own calculations using the 2000–2017 QCEW and 2000–2017 IRS SOI, and 2003–2017 LODES.

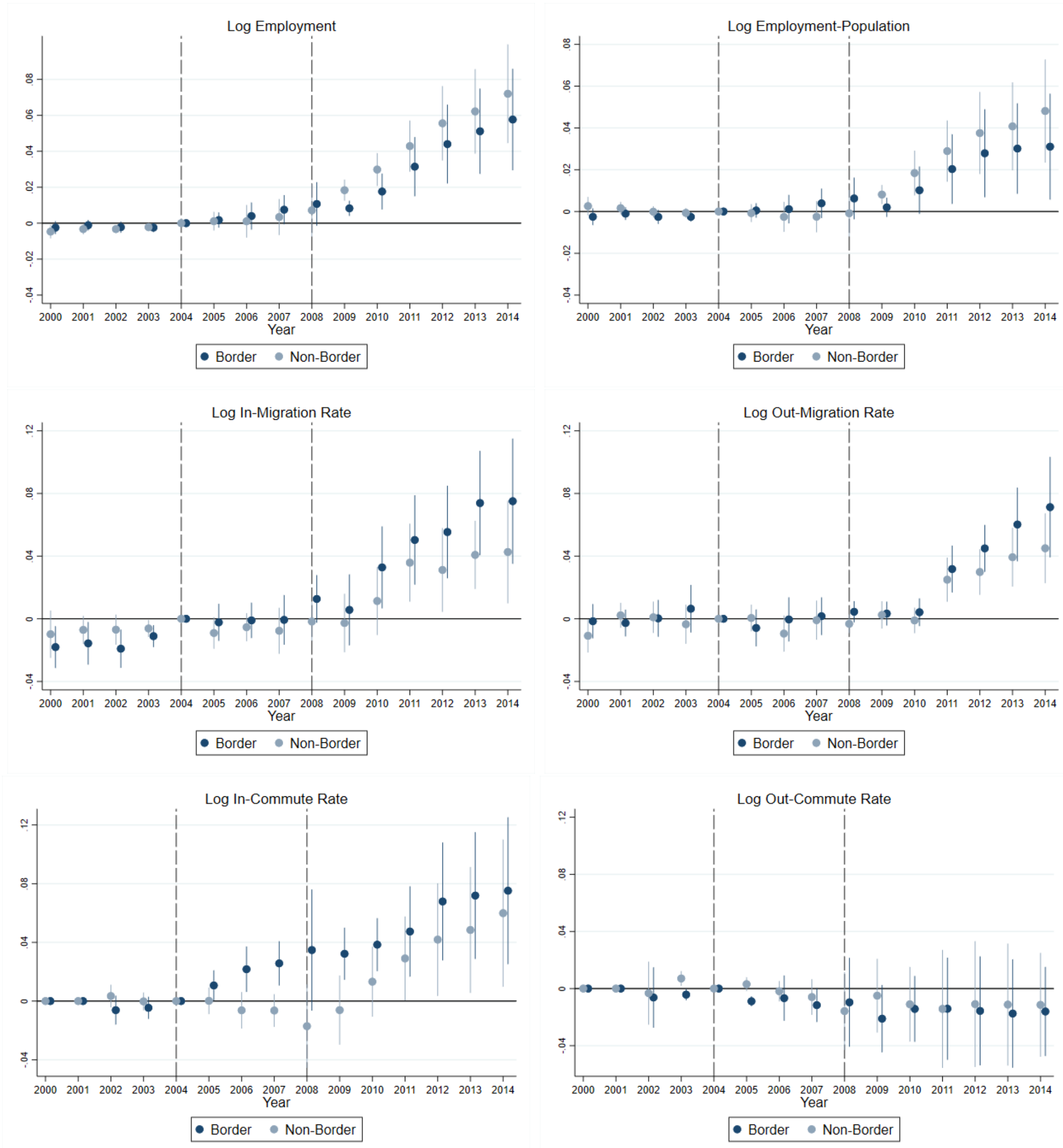
Figure A30: Impact of State Borders on Labor Market Recovery after the Great Recession, Relative to Counties on the National Border



NOTE: Event study coefficients from Equation (14) are plotted with 95 percent confidence intervals and represent the percent change in outcomes, relative to 2005, for each percentage point increase in commuting zone employment reduction between 2007 and 2009. However, counties on the national border (bordering either Canada or Mexico) are also allowed to have separate effects. Observation is at the county-by-year level. County, state-by-year fixed effects, as well as an indicator for being a border county interacted with year fixed effects, are included. Standard errors are corrected for clustering at the commuting-zone level.

SOURCE: Author's own calculations, using the 2000–2017 QCEW and 2000–2017 IRS SOI, and 2003–2017 LODES.

Figure A31: Impact of State Borders on Labor Market Impacts of Fracking



NOTE: Event study coefficients from estimation similar to Equation (14) are plotted with 95 percent confidence intervals, but rather than the change in employment from 2007–2009, the total simulated oil and gas reserves (taken from (Wilson, 2020a)) are used. Observation is at the county-by-year level. County, state-by-year fixed effects, as well as an indicator for being a border county interacted with year fixed effects, are included. Standard errors corrected for clustering at the commuting-zone level.

SOURCE: Author's own calculations using the 2000–2017 QCEW and 2000–2017 IRS SOI, and 2003–2017 LODES.

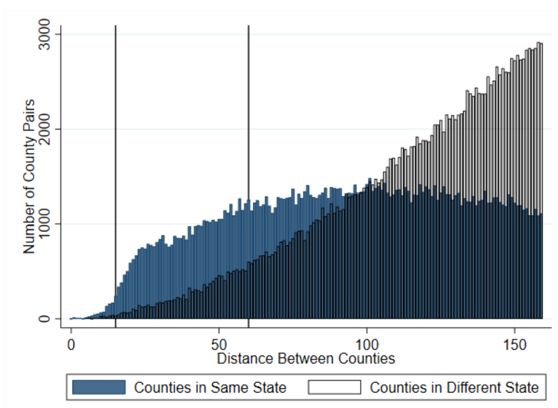
For Online Publication: Appendix B. Data Appendix

Census Bureau County Geography Files

Sources: https://www.census.gov/geographies/reference-files/2000/geo/2000-centers-population.html
https://www.census.gov/geographies/reference-files/2010/geo/county-adjacency.html

To construct the analysis sample, I first use the 2000 county population centroid file, provided by the Census Bureau. From this file, I preserve the county FIPS code and the county population centroid latitude and longitude coordinates. I then expand this data set to pairwise match each county with every other county in the United States. I then calculate the geodic distance between each county pair, and restrict the sample accordingly. For most of the analysis, I focus on county pairs that are between 15 and 60 miles apart, although in Appendix Figure A4 I extend the sample to include county pairs between 0 and 100 miles apart. The main reason I restrict the sample by distance is for interpretability. As seen in Appendix Figure B1, there are very few cross-state county pairs less than 15 miles apart. Similarly, as distance increases, the number of county pairs that are in the same state also begins to fall, and the composition of same-state pairs shifts towards larger, western states. To disentangle state border effects from compositional effects, I restrict the sample to include a common support of both within-state and across-border county pairs, between 15 and 60 miles apart. I then connect this data to the county adjacency file, provided by the Census Bureau. This file contains a list of all counties that border the focal county, allowing me to also identify neighboring counties. I then merge this data with various data sources to capture migration, commuting, and other local characteristics. Below, I describe each of the key data sets used in my analysis, as well as important characteristics of data construction.

Figure B1: Number of County Pairs by Distance



NOTE: The number of within-state and across-state county pair bins are plotted in one-mile distance bins.

SOURCE: Author's own calculations using the 2000–2017 IRS SOI and 2003–2017 LODES.

Internal Revenue Service Statistics of Income County Flows

Source: https://www.irs.gov/statistics/soi-tax-stats-migration-data

The Internal Revenue Service (IRS) Statistics of Income (SOI) division uses annual, household-level Tax Form 1040 filings to construct annual counts of county-to-county flows of individuals and households. These files provide the number of tax returns (to proxy for households) and exemptions (to proxy for individuals) that were filed in one county in year $t-1$ and in another county in year t. Most filing occurs between February and April, so annual migration flows capture moves from approximately March or April from one year to the next. For privacy purposes, the IRS suppresses county pairs that have fewer than 20 returns whose filers have moved in previous year. The suppression threshold increased from 10 to 20 returns in the 2013 data release. I record county pairs that are not observed, but that potentially have small, positive flows, as zeroes. This potentially introduces measurement error. Because I am focusing on relatively close county pairs (less than 60 miles apart), suppression is less of a concern than it would be for more distant county pairs. As seen in Appendix Figure A6, the patterns are unchanged if I limit the sample to only include nonsuppressed migration flows.

In 2011, the IRS made several changes. First, it extended the tax data collection period from September to December. As such, households that requested extensions, which tend to be higher income, were more heavily represented (Pierce, 2015). Second, the IRS also expanded the way that matches were identified to consider all heads, spouses, and dependents. Using both the new method and the old method, the IRS calculated state-level net migration rates to determine how much the series was affected. They find that 44 of the states (plus the District of Columbia) differed by less than 5 percent, and only Wyoming varied by more than 10 percent. Throughout the analysis, I focus on the cross section in 2017, so estimates are not impacted by these methodological changes over time. However, these changes might help explain the variation in Figure A2, which plots the migration estimates back to 1992.

Some moves are not captured in the IRS data. Households with low income (between \$12,000 and \$28,000 depending on age and filing status) are not required to file a Form 1040. However, many of these households will file in order to receive transfer benefits administered through the tax system, like the EITC and the child tax credit. The IRS tax data also will not capture successive moves within a year.

American Community Survey Microdata

Source: https://usa.ipums.org/usa/

The IRS county-to-county flows only provide aggregate flows, and do not provide flows for subpopulations (e.g., gender, marital status, education). To explore heterogeneous out-of-state migration, I also exploit the 2012–2017 American Community Survey Microdata obtained from IPUMS (Ruggles et al., 2019). The ACS is an annual Census Bureau survey of approximately 1 percent of households each year. In addition to collecting information about household structure, demographics (age, race/ethnicity, gender, marital status), education, and employment, it asks individuals where they lived in the previous year, making it possible to explore one-year migration patterns. The smallest geographic unit in the ACS is the Public Use Microdata Area (PUMA). PUMAs are geographic areas defined by population that is large enough to preserve privacy. Migration geographic data are only available at the Migration PUMA (MIGPUMA), which is an aggregation of PUMAs to the county level or higher, depending on population size.[33] Because MIGPUMA are often much larger than counties, the ACS data is not fit to estimate the same county-to-county flow by distance equations used with the IRS data. Instead, I focus on the probability of moving out of state, conditional on moving at all, regardless of distance to the border. In the appendix, I also examine the unconditional probability of moving out of state. I have also estimated ACS results focusing on individuals living in cross-state commuting zones (to isolate people plausibly close to the border) and find a similar pattern of results.

LEHD Origin Destination Employment Statistics Commute Data

Source: https://lehd.ces.census.gov/data/

The LEHD Origin Destination Employment Statistics (LODES) links workers' place of residence to their place of work, at the census block pair level. As such, it is possible to construct measures of commuting. Using census block to county crosswalks, I aggregate worker residence and work counts to the county level to construct county-to-county commute flows. These data are available from 2002 on, but for consistency I focus on the data from 2017. The LODES does provide some subpopulation counts, but only for broad ranges involving age (under 30, 30–54, over 54), monthly earnings (under \$1,250, \$1,250–\$3,333, over \$3,333), and industry (goods, trade/transportation, other) groups. Place of residence is missing for about 10 percent of the LEHD worker sample, and is imputed using categorical models based on sex, age, race, income, and county of work. For privacy, some noise is introduced at the census block level, which likely remains at the county level, although to a lesser extent.

[33] Only in several New England states are MIGPUMA smaller than the county level.

Social Connectedness Index from Facebook Data

Source: https://data.humdata.org/dataset/social-connectedness-index?

To capture county-to-county social ties, I use the Social Connectedness Index (SCI), constructed by Bailey et al. (2018). This measure is derived from Facebook microdata and counts the number of friendship links between each county and every other county in the United States from a snapshot of active Facebook users in 2016. An active user is "a registered Facebook user who logged in and visited Facebook through our website or a mobile device, or used our Messenger application . . . in the last 30 days" (Bailey et al., 2018). As such, I observe a static measure of each county's social network, as captured by Facebook users. At the time, there were 236 million active Facebook users in the U.S. and Canada (Bailey et al., 2018). I multiply the SCI by 400, so that the smallest reported value is 1. This number is a scalar multiple of the actual county-to-county number of friends, which is multiplied by a constant to preserve privacy. This measure has been shown to be correlated with other proxies of social networks (Bailey et al., 2018). I originally obtained it through an individual data use agreement, but the authors have since made versions of the data publicly available at the link provided above.

Pew Social Trends – October 2008 Survey

Source: https://www.pewresearch.org/social-trends/dataset/mobility/

The October 2008 Pew Social Trends was a survey of 2,260 adults living in the continental United States, conducted by Princeton Survey Research International between October 3 and 19, 2008. During the 20-minute survey, respondents were asked questions concerning place of residence, moving histories, what places they identified with, why they identified with those places, and whether they would consider moves in the future. I make use of several questions in particular. Question 17 asks what state individuals were born in. Question 9 asks, "Have you lived in or near your local community your entire life, aside from the time you may have spent away in school or college, or have you lived in other places?" With these two questions, I am able to identify individuals who have never left their birth state.

Unfortunately, individuals who have ever moved are sometimes asked slightly different questions from those who have never moved. Nonmovers are asked Question 15: "For each of the following, tell me if this was a major reason, a minor reason, or not a reason you have lived there all your life." They are then presented with various reasons, including job or business opportunities, cost of living, family ties, no desire to live someplace else, the climate, connections to friends, community involvement, "I just feel I belong here," a good place to raise children, recreational and outdoor activities, medical and health reasons, cultural activities, or "I grew up here." I split these reasons into three groups: 1) personal/social ties (family ties, connections to friends, and community involvement); 2) amenity ties (job or business opportunities, cost of living, the climate, a good place to raise children, recreational and outdoor activities, medical and health reasons, and cultural activities); and place-based identity (no desire to live someplace else, "I just feel I belong here," and "I grew up here"). The place-based identity features tie an individual to an area, but not necessarily because of local amenities or social connections in the area. I measure birth-state identity among the nonmovers as anyone who reported a place-based identity reason as a major reason for living here all his or her life.

Movers are asked Question 20, "When you think about the place you identify with the most—that is, the place in your heart you consider to be home—is it the place you live now, or is it some other place?" In a follow-up question, they are asked where that place is and which state it is in. Combining this information, I can identify movers who exhibit a birth-state identity. Movers are also asked a question, similar to Question 15 for nonmovers, but the options are different: job or business opportunities, cost of living, family ties, education or schooling, the climate, a good place to raise children, recreational and outdoor activities, medical and health reasons, cultural activities, or retirement. As such, I can only compare birth-state identity to family ties and amenity ties in Table 4.

All participants are asked in Question 38 which state they would prefer to live in, including their current state of residence. From this, I can calculate whether participants would prefer to live in their birth state. All participants are also asked in Question 8 how likely they are to move in the next five years. The sample is then randomly split into three groups, and each is asked the following: "As I read through the following places, just tell me your first reaction—Would you want to live in this city or its surrounding metropolitan area or NOT want to live there?" Participants are then given a list of 10 large metropolitan areas spread throughout the country. Because only one-third of the sample is asked each of these questions, there is not enough power to examine these separately. Instead, I create a binary outcome that equals 1 if the individual said that they were willing to move to any of the cities. From this outcome, I estimate whether birth-state identity is associated with a change in the probability of participants saying they would move to a randomized list of large MSAs.

Because birth-state identity depends on observing the individual's state of birth, foreign-born survey participants are excluded from the analysis, leading to a sample of 1,949 individuals. All regression estimates are weighted using the nationally representative survey weights provided by Pew.

Gallup Survey on Residents' Views on Own State

Source: https://news.gallup.com/poll/168653/montanans-alaskans-say-states-among-top-places-live.aspx?version=print

Between June and December 2013, Gallup conducted a survey of more than 600 residents each for every state. They specifically asked residents whether they view their state as "the best possible state to live in." Surveys were conducted by phone, and the sample is reweighted for sampling error, nonresponse, and to match state demographics. I only observe Gallup's state-level estimates of the share of residents that feel their state is the "best possible state to live in," the "best or one of the best possible states to live in," or the "worst possible state to live in."

National Cancer Institute Surveillance, Epidemiology, and End Results Program

Source: https://seer.cancer.gov/popdata/download.html

I obtain annual, county-level population estimates from the Surveillance, Epidemiology, and End Results Program (SEER). The U.S. Census Bureau provides annual single-year age population estimates at the county level to the National Cancer Institute. These estimates are available by gender and by race by origin (Hispanic vs. Non-Hispanic). These population data are used in the denominator to create migration rates, commute rates, and employment and population ratios. To construct these rates, I use the full population in the denominator. I also construct race shares; gender shares; and age shares for under 20, 20–34, 35–49, 50–64, and over 64. These are then merged to both the origin and destination counties of each county pair.

Local Area Unemployment Statistics

Source: https://download.bls.gov/pub/time.series/la/la.data.64.County

I obtain county-level labor force, employment, and unemployment levels which we use to construct unemployment rates from the BLS Local Area Unemployment Statistics. These measures are then merged to the origin county and then again to the destination county to observe differences between origin and destination counties.

Quarterly Census of Employment and Wages

Source: https://www.bls.gov/cew/downloadable-data-files.htm

I obtain county-level annual measures of employment and wage earnings by industry from the BLS Quarterly Census of Employment and Wages. I also construct employment industry shares for 10 broad industries (natural resources, construction, manufacturing, trade, information, finance, professional, education and health, hospitality, and other). These measures are then merged to both the origin and destination counties in each county pair. During this period, Shannon County, South Dakota, was changed to Oglala County. To facilitate the merge, the FIPS code for Shannon County, South Dakota (46113), is changed to the time-consistent Oglala County FIPS code (46102).

Federal Housing Finance Agency House Price Index

Source: https://www.fhfa.gov/DataTools/Downloads/Pages/House-Price-Index-Datasets.aspx#qexe

I obtain a county-level house price index from the Federal Housing Finance Agency. This is a developmental index that is not seasonally adjusted. This measure indicates how much house prices changed within an area, but because they are normalized, it does not facilitate a cross-county comparison. To create a comparable series, I collect county-level median house prices from the 2000 decennial census, then use the price index to pull county-level prices forward and backward in time. This measure is then merged to both the origin and destination county in each county pair.

2017 SUSB Annual Data Tables by Establishment Industry

Source: https://www.census.gov/data/tables/2017/econ/susb/2017-susb-annual.html

I use the 2017 Statistics of U.S. Businesses annual table to estimate the number of establishments at the county level. This measure is used to estimate strategic firm location behavior with respect to state borders. I then merge these measures to both the origin and destination counties in each county pair. The number of firms can also be captured in the QCEW and provides a similar pattern.

County Partisanship and 2016 Presidential Vote Share

Source: https://electionlab.mit.edu/data#data

I collect county voting patterns from 2000 to 2016 from the MIT Election Lab. We observe the vote share for each party in each presidential election. We keep the Republican vote share in the 2016 election. I then merge these measures to both the origin and destination counties in each county pair.

State Income Tax Burden

Source: http://users.nber.org/ taxsim/state-tax-rates/

Using state tax levels for representative taxpayers, calculated by NBER TAXSIM, I construct income tax burdens. Some states do not have state income taxes. As such, I calculate the total federal plus state income tax burden to calculate percent differences in income tax burden. Tax levels are calculated for taxpayers with income of either \$10,000, \$25,000, \$50,000, \$75,000, or \$100,000. Four different family types are considered: 1) single, 2) single/elderly, 3) joint (no dependents), and 4) joint with two dependents. We plot results for single, joint (no dependents), and joint (two dependents) at all of the income levels.

State Income Tax Reciprocity Agreements

Source: https://tax.thomsonreuters.com/blog/state-by-state-reciprocity-agreements/

As upheld by the U.S. Supreme Court in *Comptroller of the Treasury of Maryland v. Wynne* on May 15, 2015, states are not allowed to "double" tax income earned out of state. To avoid paying taxes in both your state of work and state of residence, workers must typically file tax returns in both states, with a tax credit in your state of residence for personal income tax paid in another jurisdiction. Filing taxes in both states could impose an additional hassle cost associated with cross-border commuting. Some states include tax-filing reciprocity agreements, so that workers only pay taxes based on their state of residence rather than on their state of employment. This list was provided by Thomson Reuters, but similar lists can be found elsewhere. New Jersey used to have a reciprocity agreement with Pennsylvania, but that was discontinued in December 2016, meaning Pennsylvania residents working in New Jersey would have to file taxes in both states to receive the credit.

State	States with a Reciprocity Agreement
Arizona	California, Indiana, Oregon, Virginia
Illinois	Iowa, Kentucky, Michigan, Wisconsin
Indiana	Kentucky, Michigan, Ohio, Pennsylvania, Wisconsin
Iowa	Illinois
Kentucky	Illinois, Indiana, Michigan, Ohio, Virginia, West Virginia, Wisconsin
Maryland	Pennsylvania, Virginia, Washington, D.C., West Virginia
Michigan	Illinois, Indiana, Kentucky, Minnesota, Ohio, Wisconsin
Minnesota	Michigan, North Dakota
Montana	North Dakota
North Dakota	Minnesota, Montana
Ohio	Indiana, Kentucky, Michigan, Pennsylvania, West Virginia
Pennsylvania	Indiana, Maryland, New Jersey, Ohio, Virginia, West Virginia
Virginia	Kentucky, Maryland, Pennsylvania, Washington, D.C., West Virginia
Washington, D.C.	Maryland, Virginia
West Virginia	Kentucky, Maryland, Ohio, Pennsylvania, Virginia
Wisconsin	Illinois, Indiana, Kentucky, Michigan

State Minimum Wages

Source: https://www.dol.gov/agencies/whd/state/minimum-wage/history

State minimum wages for 2017 are obtained from the U.S. Department of Labor. Some state minimum wages are not universal, but rather apply to certain firm sizes. I keep the most universal minimum wage for each state and merge this to both the origin and destination counties. For states without a state specific statute, the federal minimum wage is used.

State EITC Supplement Rate

Source: https://users.nber.org/ taxsim/state-eitc.html

I collect state EITC supplement rates from the NBER for the year 2017. For most states, these rates are percentage supplements to the federal EITC rate. There are several exceptions. The California rate only applies to the phase-in region (until about $22,300 for households with children in 2017). The rate is Wisconsin depends on the number of qualifying depends, for Wisconsin I keep the lowest rate of 4 percent. I include both refundable and non-refundable credits.

State TANF Benefit Levels

Source: https://fas.org/sgp/crs/misc/RL32760.pdf

State Temporary Aid for Needy Families (TANF) maximum monthly benefit levels for a single-parent family with two children are collected from Congressional Research Services, from March 2018. TANF is distributed to states through a block grant, and states have flexibility over how these funds are used.

State by State Medicaid Expansion

Source: https://www.kff.org/medicaid/issue-brief/status-of-state-medicaid-expansion-decisions-interactive-map/

As part of the Affordable Care Act, states were allowed to expand Medicaid to include low-income adults up to 138% of the federal poverty level. I collect records of states that had expanded Medicaid by December, 2017 from the Kaiser Family Foundation.

Pre-K Through 12 Public School Expenditures per Pupil

Source: https://ncses.nsf.gov/indicators/states/indicator/public-school-per-pupil-expenditures/table

I obtain county-level annual Pre-kindergarten through 12th grade public school spending per pupil from the National Science Board, with statistics originally produced by the US Department of Education, National Center for Education Statistics. The measure captures local, state, and federal spending on elementary and secondary education, divided by pre-kindergarten through 12th grade public school enrollment. I then merge this measure to both the origin and destination counties in each county pair.

State Sales Tax Rates

Source: https://taxfoundation.org/state-and-local-sales-tax-rates-in-2017/

I obtain state sales tax rates from the Tax Foundation for the year 2017. Average and maximum local sales tax rates are also provided, but there is no indication of what counties these measures apply to. Some states do not have sales tax. These measures are merged to both the origin and destination counties in each county pair.

State Corporate Income Tax Rates

Source: https://taxfoundation.org/state-corporate-income-tax-rates-brackets-2017/

I obtain state corporate income tax rates from the Tax Foundation for the year 2017. Some states have a single corporate income tax rates, others have a progressive schedule of rates ranging from 0 to 12 percent. For each state I keep the maximum corporate income tax rate. This is then merged to both the origin and destination county to determine if migration and commuting patterns differ when the potential destination has higher or lower corporate tax rates.

Stanford Education Data Archive County-level Test Scores Version 4.1

Source:https://edopportunity.org/get-the-data/seda-archive-downloads/

County-level, standardized math and reading language arts (RLA) test scores are obtained through the Stanford Education Data Archive (Fahle et al., 2021). These estimates provide measures of standardized test achievement for students from 3rd to 8th grade between 2008 and 2018. I use the county-level pooled by subject Bayesian Estimation estimates which average across all cohorts and years. These test scores are derived from each state's mandatory testing and are obtained through ED*Facts* at the U.S. Department of Education. These scores are then mapped into a common scored exam, the National Assessment of Educational Progress (NAEP) using Heteroskedasticity Ordered Probit models. The pooled mean estimates are obtained through hierarchical linear modeling. I include the residual shrinking Empirical Bayes estimates.

Shoag, Tuttle, and Veuger (2019) Home Rule

Source: Obtained from the authors

I obtain measures of "home rule" or within state county-powers from (Shoag et al., 2019). This measure captures the amount of county autonomy which might be related to state identity or individuality.